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Data envelopment analysis as a benchmarking application for humanitarian organizations

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DATA ENVELOPMENT ANALYSIS AS A BENCHMARKING APPLICATION FOR HUMANITARIAN ORGANIZATIONS

A dissertation submitted in partial satisfaction

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Doctor of Philosophy in Global Leadership and Change

by

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DEDICATION

This dissertation is dedicated to my family and friends, who provided continuous support and motivation through this dissertation journey.

ACKNOWLEDGMENTS

A special thanks to Dr. Rhodes, Dr. Leigh, and Dr. Gollhofer for their tireless support, patience, dedication, and motivation to complete this dissertation journey. I also would like to thank Dr. Thanassoulis and Dr. Emrouzenjad for the DEA course and counsel supporting my continued education in the Data Envelopment Analysis methodology. In addition, I want to acknowledge the faculty and staff who provided the building blocks and support at Pepperdine University that has brought me to this point in my educational journey. I also wish to thank the client for their support in my dissertation. Lastly, my partner, children, and parents gave me confidence and inspiration in this endeavor.

VITA

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STRATEGY & PERFORMANCE IMPROVEMENT EXPERT

Experienced strategy, performance, and process improvement expert with proven capability to drive enterprise-wide strategic planning, management, and process improvement initiatives. Customer-centric focused on delivering customized solutions providing significant improvements to quality, speed, and cost. Recognized expert in Continuous Process Improvement (CPI) methods, program management, strategic planning, End-to-End process mapping, and statistical and root cause analysis. Functional areas of expertise include business operations, human resources, financial management, and policy development.

Core Competencies

- Leadership
- Strategic Planning
- Program/Project Management
- Enterprise Process Improvement
- Business Transformation
- Change Management
- Business Process Reengineering (BPR)
- Lean and Six Sigma
- Statistical & Root Cause Analysis
- BPMN 2.0 & Value Stream Analysis
- Kaizen/RIE (Rapid Improvement Event)
- Certified Instructor

PROFESSIONAL EXPERIENCE

International Medical Corps – Los Angeles, CA September 2015-Present
Senior Director, Business Optimization

Performance Improvement, Business Analytics, Internal Audits, Grants & Contract Management

Reporting to the COO and CFO of international humanitarian NGO with 7,500 staff, programs in 30 countries, and an annual budget of $350 million. Oversee standardization, process improvement, and rollout of new systems to measure performance, improve business operations, and maximize efficiency and impact.

Developed the International Operations Standard Operating Procedures (SOP) to improve standardization across operational lines of business in the daily execution of mission requirements. Design and implement processes and policies in response to Human Resources for overseas screening, recruitment, and assignment. Resolved over 400 programmatic internal audit findings in 2021 that consisted of procurement, human resources, program operations. Assisted and supported grants and contract management supporting five countries with a portfolio of $73 million. Standardize GIS mapping production in support of worldwide operations.

DEPARTMENT OF DEFENSE – Arlington, VA May 2012- September 2015
Office of the Deputy Chief Management Officer (ODCMO)
Management Analyst, Master Black Belt

DoD Business Optimization Division: Provided direct support to the Division Director and conducted day-to-day operations for a 13-person division consisting of senior DoD civilians (GS-15 level) and contract staff. Weekly interaction with senior DoD leadership providing updates to current projects and developing new opportunities. Instructed the staff on implementing the Service Development and Delivery Process methodology. Led high-visibility projects with congressional interest and enterprise-wide impact. Performed human resources and contract management functions, reviewed staff project deliverables, and responded to leadership tasks on behalf of the Division Director.

Performance Improvement Expert. Designed and implemented processes and policies in response to overseas screening and assignment of military-dependent children. This ensured all DoD component organizations (military and civilian alike) complied with strict approval and reporting requirements. Prepared and published congressionally required reports on behalf of the Director of DOD Education Activity (DoDEA). Drafted responses to congressional inquiries and proposed legislative actions. Provided multiple briefings to the DoDEA.

Security Investigations Expert: Led the planning and development for alternatives to implementing Federal Investigation Standards 2012 (FIS2012) for the Department of Defense Central Adjudication Facility (DODCAF). The personnel security program was an $800 million program annually and aligned with the IRTPA law, strategic goals, performance goals, and measures. As part of this effort, I provided numerous briefings to the senior leadership of the DCMO and the Secretary of Defense.

United States Marine Corps - Quantico, VA May 2006-June 2012
Marine Corps Intelligence Activity
Commanding Officer, Operations Officer, Deputy Geospatial Intelligence Division & Production Manager

Responsible for monitoring production efforts across the Production and Analysis Command. Ensured that applicable Intelligence Community Directives, DoD, USMC, and command policies were implemented and adhered to in support of collections, analysis, and production efforts. Provided oversight of four separate production entities; Regional Analysis Directorate, Geospatial directorate, Weapons & Tech division, and Quality Assurance and Dissemination. Ensured that fused intelligence has collaborated internally and with broader Intelligence Community and nontraditional partners.

Led and designed MCIA continuous process improvement efforts. Streamlined quality assurance process, which improved a cycle time of 50% within the first quarter of operation. Further improved cycle time performance with the implementation of the SAVANT system for the entire analytical production process. In many product categories, cycle time decreased from 47 to 8 days, nearly a six-fold increase in performance and a substantial increase in quality, based on analytical integrity and standards.

The United States Marine Corps July 1989-July 2009
Marine Officer

Twenty years of leadership, from small organizational elements to headquarters level commands. Worldwide experiences ranging from Bosnia, Korea, Iraq, and Afghanistan. Led Marines on several deployments to Iraq, supporting air, ground, and logistics operations. A principal intelligence staff officer for aviation operations in Iraq. Primary intelligence planner for United States Forces in Korea. Additional experiences include a F/A-18 pilot and Space Operations certifications. Tremendous knowledge in analysis, collections, targeting, operational planning, and information-sharing. Handpicked for numerous high-visibility, high-pressure positions.

EDUCATION

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Marine Command and Staff College (Nonresident) Quantico, VA	**June 2001**
B.A., University of Utah, Salt Lake City, UT	**April 1989**

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Office of the Secretary of Defense Lean Six Sigma Master Black Belt	**May 2012**
DoD Executive Potential Program	**March 2012**
Planning, Programming, Budgeting, and Execution (Army)	**April 2009**
Office of the Secretary of Defense Lean Six Sigma Black Belt	**June 2009**
Naval Intelligence Business Executive Course	**April 2008**
Advanced Space Operations Course	**December 2004**
National Systems Technical Course	**September 2001**
Joint Targeting Weaponeering Course	**May 2000**
Joint Intelligence Collections Management Course	**May 1998**
Weapons and Tactics Instructor Course	**April 1995**
MAGTF Intelligence Officer Course	**October 1994**
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Intermediate and Advanced Jet Training	**September 1992**

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Defense Meritorious Service Medal	**March 2003**
Meritorious Service Medal	**July 2001, June 2007, May 2009**
Joint Commendation Medal	**April 1997**
Navy Marine Corps Commendation Medal	**September 1997**
Joint Achievement Medal	**February 2002**
Navy Marine Achievement Medal	**July 1995, October 2003, March 2005**

ABSTRACT

Humanitarian aid organizations are under tremendous pressure and competition for donor funds to sustain their operations. However, donor contribution levels have remained relatively stagnant over the past five years and are unlikely to grow in the foreseeable future. Additionally, donor policies and mandates have added pressure on humanitarian aid organizations to comply with new and more complex requirements.

Many humanitarian aid organizations work in some of the most challenging areas of the world, where conflict, famine, environmental, economic, and cultural challenges are prevalent. Given all these factors, a novel form of performance and efficiency measurement is needed to evaluate the performance of humanitarian aid organizations. This study addressed the possible use of Data Envelopment Analysis that measures the efficiency of an organization’s country programs. Limited funding from donors, competition, and the humanitarian imperative to reach people in need requires humanitarian aid organizations to become better and more effective stewards of donor contributions.

This study used a mixed methods approach to compare and evaluate the efficiency of the country portfolios of a humanitarian aid organization using DEA. The DEA models used are CRS and VRS using an output orientation. This study used an explanatory sequential design. First, a quantitative approach using DEA was employed to compare the efficiency of an organization’s country portfolios. Second, a qualitative effort consisted of a focus group of DEA researchers who have performed DEA on humanitarian aid programs. The focus group addressed the views, perspectives, and issues of conducting DEA within the humanitarian sector.

The DEA study was conducted in three phases. A sample of 19 country portfolios was used in this study. The results showed that 10% of the countries were efficient in the aggregate under a CRS model, and 20% using a VRS model.

The focus group provided insights and perceptions for DEA from a practical perspective. These were categorized from technical requirements and communications with a client. The challenge in the humanitarian sector is that DEA is not a well known methodology. An explanation is often required on what DEA can do for an organization and its limitations. Additionally, an explanation was often needed for a client to understand how decision making units (DMUs), variables, and DEA techniques can be used to support a humanitarian aid organization.

Keywords: Data Envelopment Analysis, DEA, humanitarian aid, efficiency, benchmarking

Chapter 1. Introduction

The movie *Moneyball*, based on the best-selling book by Michael Lewis (Sherman & Zhu, 2013), depicted how the Oakland A's baseball team employed statistical analysis to build a championship team out of undervalued baseball players. A key lesson from both the book and movie was that statistical strength, not subjective impressions and decision making, can more accurately determine how a player will perform (Sherman & Zhu, 2013). The same can be said for how humanitarian organizations assess leadership and operations. Traditionally, these organizations look broadly for experience and a person's curriculum vitae. However, they also rely on intuition and subjective assessments when these will go only so far in the dynamic and complex environments where humanitarian aid organizations operate.

This study investigated the utility of Data Envelopment Analysis (DEA) as a benchmarking instrument to measure the efficiency of a humanitarian aid organization, commonly called International Non-Governmental Organization (INGO). For this study, the INGO ("organization") was founded over 35 years ago and operates in about 20 countries today. The challenge for many INGOs is to provide humanitarian services to their beneficiaries and meet donor requirements. INGOs must complete the schedule, cost, and delivery requirements prescribed in the grant agreements to satisfy donors and beneficiaries.

Donors

The preponderance of INGO funding is in the form of grants. Donor grants that support humanitarian programs often require best effort. This implies soft goals and outcomes for a project, recognizing the difficulty of implementing humanitarian programs in challenging environments. This perspective, however, is beginning to shift in recent years, particularly with United States (U.S.), European Union (EU), and United Kingdom (U.K.) government donors.

The United States, for instance, has recently changed this paradigm. The Office of Management and Budget (OMB) has mandated that organizations receiving support from the U.S. government be graded on their performance as stipulated within the awarded grant (United States Office of Management and Budget, 2020). The performance metrics will soon become more defined and specific with stated performance criteria and expectations. Additionally, government agencies overseeing these grants will develop a performance dashboard to assess those organizations that receive grants from the U.S. government (United States Office of Management and Budget, 2020). While these new requirements put added, possibly onerous pressure on organizations to report their activities, before these new measures, inefficient INGOs might still win grants, and there was little incentive to improve their practices (Light, 2000).

Donor governments are not the only ones that impose strict compliance guidelines for implementing humanitarian grants. United Nations (UN) organizations that provide grant funding require INGOs to adhere to the agreed-upon standards in grants between them and UN agencies (Mommers & Van Wessel, 2009). Reimbursement of costs is dependent on the implementation of the agreed-upon standards. This ensures accountability for the funds received by the INGO for project implementation and the quality of the program (Mommers & Van Wessel, 2009).

INGO leaders are under pressure to lower costs and improve the quality of the services and delivery of their program efforts (Kaplan & Porter, 2011). The difficulty is determining the efficiency of INGO programming. Generally, time, money, and quality are the driving factors in program implementation. Most classifications have been reduced to an INGO’s fiscal or operational activities (Ospina et al., 2002). However, this can prove an overly simplistic measurement regarding analysis and decision-making for INGO leaders and organizations. These organizations must address the immediate results and impact of their program efforts and demonstrate the longer-term stewardship of the resources provided to them (Light, 2000).

Linear Programming

Soviet mathematician Leonid Kantorovich and the American economist Wassily Leontief first attempted linear programming in the late 1930s. Initially, their efforts were largely ignored until World War II. During World War II, linear programming became prevalent in the war effort to enhance logistics, production, and resource allocation (Gregersen, 2017). Over the years since World War II, economists and mathematicians have developed and used linear programming techniques. Kantorovich and T. C. Koopman (economist) resolved many economic problems using linear programming models. Both were later awarded the Nobel prize for economics in 1975 (Sierksma & Zwols, 2015).

Linear programming is a mathematical modeling technique where a linear function is minimized or maximized based on the various constraints. Linear programming techniques support quantitative decisions in business planning, operational research, and industrial engineering (Gregersen, 2017). Many companies rely on linear programming techniques to maximize profits and minimize costs from a practical approach.

Data Envelopment Analysis (DEA)

Data Envelopment Analysis is a linear programming framework developed by Charnes et al. (1978). DEA can consider the different organizational or environmental constructs in developing an efficiency score and provides a frontier for those best practices (Medina-Borja, 2000). However, many INGOs do not monitor or evaluate their operations holistically, perhaps viewing the circumstances of the environments where they operate to be too complex to implement a scientific or mathematical evaluation of those operations.

DEA can measure multiple inputs and outputs from several entities within or outside an organization. These departments or entities are referred to as the Decision Making Units or DMUs. DEA processes the various inputs and outputs for each DMU. DEA envelops the data and then provides an efficiency score to each DMU. A score of 1.00 indicates that the DMU is efficient compared to other peer DMUs. A score that is less than 1.00 (< 1.00) is inefficient. The efficiency can provide insights into the organization's practices and procedures based on the measured inputs and outputs. DEA can measure and evaluate an INGO's efficiency down to the country level and further below. An organization that utilizes DEA methodology can evaluate and model country best practices and identify inefficient areas for improvement.

Organizations may choose what variables (inputs and outputs) to utilize when performing DEA analysis. Inputs can be the number of staff, cost of the materials, or time to produce a product. Outputs variables can be from a fiscal perspective (e.g., profits or revenue generation, or the number of products made). In this study, the primary variables used were direct costs (budget) of the country portfolio, staff, and the beneficiaries served during the observation period. Ultimately the standard scale in DEA determines how DMUs are efficient among homogenous units. The scale of efficiency is 1.00, meaning that the DMU is efficient. Less than (< 1.00) determines that the DMU is inefficient compared to the efficient DMU.

The organization to be studied in this effort regularly produces standardized metrics and reports these aid programs. The metrics are reported to their donors and other stakeholders. An example is financial reports that provide the funding utilized in the lifecycle of a humanitarian aid program. Another example is the reports demonstrating the number of beneficiaries who receive support and services from an NGO. These metrics are standard reports for many donors and international organizations.

Currently, measurement systems consist of management and program implementation metrics. The management perspective may view the inputs as financial, procedural, or process-oriented measures (e.g., the burn rate of donor funds, the number of procurements active, or the current status of a work plan). Conversely, the program implementation side may measure quality vis-à-vis outcomes (e.g., how many patients were seen at a health clinic, the number of vaccinations provided, or the number of staff who received training). There is overlap between the management and outcome measurement approaches. However, these can become silos and be disconnected from a holistic evaluation of a country's portfolio at large.

This study used the direct costs (budget), staff, beneficiaries as the primary variables. The direct cost variable was an input variable. The direct cost variable was the actual dollar value used to operate the country portfolio for 2020. The staff variable was an input variable. The staff variable was the average number of staff (employees, consultants, and volunteers) who implemented the number of programs for 2020. Under the DEA methodology, these are considered discretionary variables. Therefore, a discretionary variable was one where the management team can decide how the variables are used. Finally, the output variable was the number of beneficiaries served. The beneficiaries served were individuals who received treatment, services, or training during the various programs that encompass the countries portfolio during the calendar year 2020.

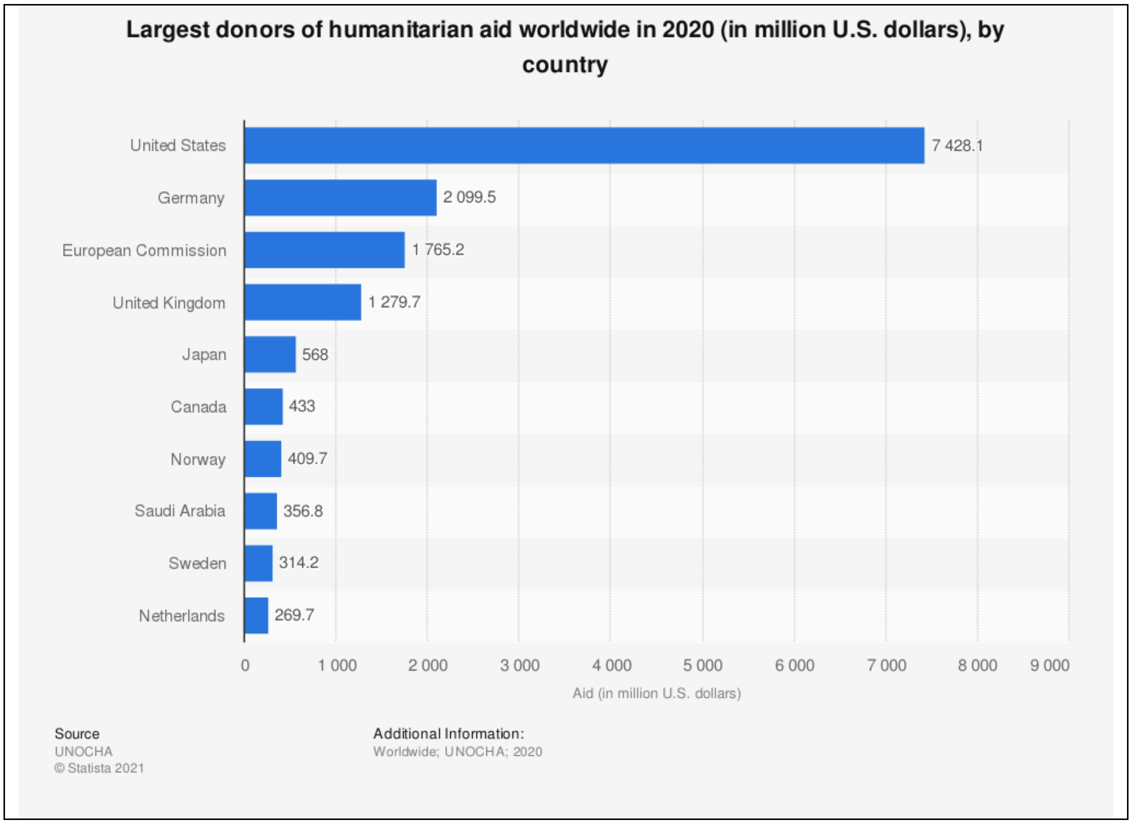
Additionally, this research included corruption and conflict variables that are considered nondiscretionary. These were nondiscretionary because the country management team cannot influence or change these variables. The conflict variable was derived from the University of Gothenburg, Quality of Government Standard Dataset (Toerell et al., 2021). The corruption variable was derived from Transparency International (2021).

Statement of the Problem

Measuring multiple inputs and outputs through DEA methodologies is not new; the commercial and industrial sectors have utilized DEA to measure efficiency for many years. Yet, few studies have been conducted on NGOs' efficiency using DEA applications (Alda & Cuesta, 2019; Martin-Perez & Martin-Cruz, 2017; Medina-Borja, 2002). The Organization for Economic Co-operation and Development (O, 2018) estimated humanitarian aid at $178 billion U.S. per year. In 2021 the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA, 2021a) indicated that the top ten donor countries contributed $17.3 billion (U.S. dollars). The United States contributed $7.4 billion to humanitarian efforts, followed by Germany with $2.9 billion U.S. See Figure 1 for the top ten contributors for humanitarian support.

Figure 1

Largest Donors of Humanitarian Aid Worldwide in 2020



Note. UNOCHA (2021a). Largest donors of humanitarian aid worldwide in 2020 (in million U.S. dollars). (https://www.statista.com/statistics/275597/largers-donor-countries-of-aid-worldwide/). In the public domain.

To put this funding into context, the $7.428 billion for humanitarian aid accounts for nearly 28% of the U.S. State Department's total budget for 2021 (Unites States Office of Management and Budget, 2020). The portion of the overall U.S. government annual budget allocated to foreign aid is < 1% (Ingram, 2019). Other countries (Norway, Sweden, Luxembourg, Denmark, and the U.K.) contribute 1% of their annual budgets (Ingram, 2019). Donor grants and funding is becoming more competitive within the humanitarian sector. It was estimated that there were over 40,000 NGOs in 2013 (Ben-Ari, 2013). The growth of nonprofits continues each year. In some countries, the growth of nonprofits is passing the gross domestic product (GDP). In

Australia, nonprofits' annual growth rate is 11%, compared to 7.5% of Australia's annual GDP (Soysa et al., 2019).

The need for and impact of this assistance is clear. According to UNOCHA (2021b), $5.8 billion alone are required to support United Nations operations in West and Central Africa for 2021. However, only $2.8 million (5%) has been provided as of April 6, 2021 (UNOCHA, 2021b). Additionally, from 2015 to 2020, there has been a funding shortfall between 51% to 57% (UNOCHA, 2021b). This illustrates that the lack of funding will ultimately affect humanitarian operations, and NGOs must effectively use their limited resources.

The capabilities of each INGO differ. Larger INGOs can provide a broad-sector approach toward delivering emergency relief, health care, education, economic development, or social justice. Smaller INGOs tend to focus on a specific sector. In an increasingly competitive landscape, with limited funding available and increased transparency requirements from donors, INGOs must become more efficient within their respective country operations, identify those best practices, and replicate best practices with other country program portfolios. In addition, it is incumbent on those INGOs to produce the results agreed upon in the grant proposal and be responsible stewards of the monies provided to them. DEA is a potentially robust methodology that can provide INGOs with an approach to remedy those internal challenges once they have been identified.

Purpose Statement

This research aimed to benchmark and measure the efficiency of an International NGO. This study used an explanatory sequential mixed methods design (Creswell & Creswell, 2018). The first element of this design was collecting quantitative data from the organization, the Quality of Government Standard Dataset (Toerell et al., 2021), and Transparency International

(2021). The quantitative instrument was PIM DEA to analyze the variables from the organization and derive an efficiency score from the organization's country portfolios. From this initial investigation, I used a qualitative approach to investigate the views, perspectives, and impacts using a DEA methodology for humanitarian organizations. I used a focus group that has used a DEA approach to evaluate humanitarian aid programs.

In this study, I used the pseudonym for the NGO, "organization." The organization is currently operational in 19 countries, primarily in the Middle East, Africa, and Southwest Asia. This study aims to identify those factors that contribute to an efficient score compared to other peer country programs within the organization. Additionally, this research is to understand better the impact of the variables to be measured relating to the efficiency of the organization's country operations.

The data were collected from the organization's data systems. The analysis for this study was conducted in three phases. Phase I examined business data from each country or DMU. The variables collected were for calendar year 2020. The input variables collected were operational country budgets (financial) and human resources (staff). The outcome variable was the number of beneficiaries served. Additionally, 2020 was the year of COVID-19, when many countries quarantined and implemented travel restrictions, curfews, and other measures to contain the spread of the virus.

Phase II disaggregated the DMUs into their respective regional areas (Middle East, West Africa, and East Africa/Asia). The purpose was to evaluate and compare the DMUs within the context of their regional areas.

Phase III of this investigation explored external contributing or contextual factors that may affect the efficiency of these humanitarian efforts. These variables consisted of corruption and conflict indices. These external variables provided context to the environmental and social dynamics where the organization currently operates. A study was conducted by Alda and Cuesta (2019) utilizing a DEA approach to analyze the contextual factors for humanitarian aid for 107 countries. These factors were derived from Transparency International and the Quality of Government Institute (University of Gothenburg) databases.

Humanitarian aid is ultimately a business that is crowded with many competitors. There is a finite amount of donor funding that grant organizations can disperse. As previously discussed, INGOs use many variables to monitor their activities that may or may not be holistically reviewed. Although many donors are partners with INGOs and may be sympathetic toward these INGOs' environments, the tide is shifting for accountability and responsibility as stewards of the monies provided to an INGO.

DEA Utilization in the Commercial Sector

DEA was first introduced in 1978 (Charnes et al., 1978). Researchers from many fields have recognized DEA methodology as an instrument for modeling performance evaluations and measuring efficiency. From DEA's inception in 1978, DEA has been enhanced through additional developments over the past 40 years (Cooper, Seiford, et al., 2011).

DEA has been used in many other commercial and private sectors over the last 40 years. These consist of education, health care, banking, merchant shipping, supply chain, and pollution reduction, to name a few. DEA allows an organization to measure the different sizes and elements that are benchmarked in relative terms among those peer elements. The elegance of DEA is that one can now compare the apples, oranges, grapes of organizational departments that differ in size, staffing, and other resources. A researcher or practitioner can evaluate these organizational entities within the DEA framework.

DEA was first used to study the efficiency of a Texas school system by Charnes et al. (1978). Since Charnes et al.'s seminal work, many adaptations and modifications have occurred. Over time, it has been an evolution that has met the needs of many other industries, and DEA continues to be growing in use.

In 1983, Nunamaker applied DEA toward the health care system, measuring nursing services' efficiency (as cited in Gollhofer, 2015). The DEA methodology has been used to measure healthcare, comparing teaching and nonteaching hospitals (O'Neill, 1998). In Turkey, a study was conducted to explore the operational performance of 352 hospitals from 2005 to 2008 as a part of a national health transformation initiative (Sahin et al., 2009). The state of Virginia reviewed hospitals' technical quality and efficiency that demonstrated that DEA could be applied in both cases (Nayar & Ozcan, 2008).

The banking industry has been utilizing DEA for many years. Not all bank branches are the same or created equal. Bank branches differ in physical size, the number of staff, volume of personal and business transactions, loans and mortgages, and other areas. DEA use in the banking industry has been observed globally. In Saudi Arabia, for example, DEA was used to determine the efficiency of Saudi banks from 2003-2008 (AlKhathlan & Malik, 2010). Saudi Arabia has several various financial systems that are bank-centric. AlKhathlan and Malik (2010) demonstrated that the banking system managed its financial resources well and provided critical information for regulators and investors.

In more recent years, the emphasis on climate change and reduction of carbon emissions has prompted interest in the use of DEA in this area. Practitioners of DEA conducted a literature review evaluating the usefulness of DEA in pollution reduction by the volume of peer-reviewed articles and the diversity of the subject matter (Zhou et al., 2017).

Recently, the shipping industry conducted benchmarking analysis for the efficiency of ports and attempts to identify the key contributors of efficiency for port operations (Minum, 2020). Although efficiency scoring strives for a 1.00, optimal values less than 1.00 may be adequate, assuming there is a balance in other port services (Minum, 2020).

DEA Utilization in the Nonprofit Sector

The above demonstrates the multiple areas where DEA has been applied in the commercial sector. Therefore, it is compelling for nonprofits and NGOs to utilize the DEA framework. There have been examples of how DEA has been used in this research, but it has not been prolific compared to the commercial sectors.

In a different example, Brazilian soccer clubs (nonprofit teams) were analyzed to determine which teams were efficient and the critical factors that presented the most significant influence for success. The nonprofit soccer teams are developmental organizations for their professional leagues and national teams (Miragaia et al., 2016). In Brazil, soccer is the national sport that has seen several World Cup champions. Soccer in Brazil isn’t just a sport but a matter of national pride.

Lukac and Mihalik (2018) discussed effectively applying museum marketing strategies using DEA. In particular, they question the outcome results given the advertising and fundraising costs from a strategic perspective. They attempt to formulate an assessment of the communication efficiency for museums.

One of the few articles discovered to date that is explicitly focused on an NGO is from Medina-Bjora (2002). Medina-Borja studied the efficiency of an NGO using DEA, applying an in-depth analysis, using four phases of DEA to capture efficiency from many factors and outcomes.

Spain's Agency for International Cooperation for Development provided funding to many INGOs and reviewed the efficiency of 48 humanitarian projects from 2001-2006. In addition, they used DEA to evaluate these programs from an efficiency perspective (Martin-Perez & Martin-Cruz, 2017).

Potential grant donors have used DEA as a selection tool for grant awards. An example is a technology company based in the mid-Atlantic states (Maryland, Virginia, and Washington D.C. region) that applied DEA as a selection method. The technology company applied DEA principles to select a high school that focuses on science, technology, engineering, and mathematics (STEM) curriculum. The company's philanthropic foundation sought to provide STEM funding and classroom support to the most deserving high school. The justification for applying DEA was to take the emotion and subjectivity out of the selection process (Partovi, 2011).

Benchmarking

This research study attempted to demonstrate that DEA can be applied as a benchmarking management tool. This will be a change in the cultural mindset for the organization. Sherman and Zhu (2013) described using DEA as an approach to "balanced benchmarking" (p. 38). Balanced benchmarking is a way to identify top performer best practices and transfer knowledge to under-performing groups. In this research effort, the challenge was implementing DEA within the organization, analyzing the results, and identifying top performers. However, replicating those activities to those who may be underperforming is out of scope for this endeavor.

Performance evaluation is essential for INGOs to stay competitive within the humanitarian sector. Therefore, benchmarking combined with performance evaluation may be prudent for INGOs to remain relevant and prosper within the competitive arena of the humanitarian sector. There are three key areas where DEA as a benchmarking application would provide added value if performed correctly: (a) identify strengths and weaknesses within the organization to the processes, activities, and operations; (b) prepare the organization to meet future or emerging donor or beneficiary needs; and (c) identify new opportunities that improve processes, operations, and new services.

Methodological Approach

This study used a mixed methods approach, which was an explanatory sequential design (Creswell & Creswell, 2018). The quantitative methodology applied DEA in three stages. First, the study determined the efficiency of the organizations using the variables described previously. The study collected the business data and financial resources (budget), staffing (personnel), and beneficiaries for an initial evaluation of the country team's efficiency levels in the aggregate across the organization's international operations. Second, the country teams were disaggregated based on the organization's areas of responsibility geographically (Middle East, West Africa, etc.). Lastly, contextual data (conflict and corruption) were added to determine the efficiency within the peer countries, given the austere and sometimes volatile environments where the country teams operate.

Additionally, the study identified areas of improvement for each country's operation. In this study, the efficiency of each country's program was determined using DEA. In general terms, efficiency uses the number of inputs for a given output. Conversely, performance measurement is often the completion by the number of indicators that the donor has prescribed in the agreed grant proposal (Shaw, 2003).

The DEA instrument for application utilized PIM DEA Software, which was acquired to calculate the DEA efficiency variables and score in this research. Additionally, Jamovi and Minitab 19 were used for statistical analysis.

Upon completing the DEA study, a qualitative approach was used to determine the potential issues from previous DEA studies on humanitarian aid programs. This approach used a focus group consisting of researchers who have applied DEA investigating other humanitarian aid programs.

Zoom virtual meeting, TEMI transcription, and MAXQDA software were used. Zoom was used to conduct the focus group. The zoom audio recording was uploaded in the TEMI software. TEMI transcribed the focus group discussion. The TEMI transcription was uploaded in the MAXQDA software and was used to analyze the discussion from the focus group.

The results from the DEA analysis and focus group discussion were combined to interpret this study. Unfortunately, DEA has rarely been used to analyze NGOs and humanitarian aid programs. As a result, the perspectives and insights regarding the use of DEA towards NGOs, humanitarian aid programs, and donors have rarely been captured. This is a gap that this study attempted to fill.

Researcher Assumptions

This assumes that the organization's business data were objectively portrayed and delivered without any missing data elements. Each functional department provided the necessary data elements within its operating authority. If missing data were discovered, I contacted the applicable department to resolve the missing data. These data have been provided to multiple donors and delivered to the organization's board of directors each quarter. Therefore, one can assume that the information is correct upon submission.

The external data sources were collected from their respective organizations' websites and databases. This is public information from the respective websites. Therefore, it is assumed that the data for conflict and corruption indices are complete, and there is no missing information for the countries in this study.

It is assumed that the participants in the focus group discussion voluntarily took part in this study.

Delimitations of Study

The scope of this research was to determine the viability of using DEA as a management or benchmarking application. The primary effort was to determine the efficiency, peer comparisons, slack, and potential target areas for improvement of the country portfolios of the organization being studied. DEA is a linear programming model not a statistical application. There are issues and DEA challenges related to the central limit theorem, correlation and other statistical analysis. Therefore, no statistical test was performed in this study.

A focus group with experts in the science and application of DEA was performed. These experts were from academia, have written or conducted studies using DEA. No surveys and questionnaires were used in this study. Language and cultural norms could be a challenge due to the diversity in this area and would be time-consuming and costly for translation services in multiple languages. The longitudinal data collected were used to objectively review the efficiency of the organizations' operations based on reporting the data from their business management systems.

Many DEA variations could be applied in this study. However, the basic Constant Returns of Scale (CRS; Banker et al., 2004; Charnes et al., 1978) and the Variable Return Scale (VRS; Banker et al., 1985, 2004) were the primary DEA applications. Malmquist, network analysis, and other DEA applications were not applied in this effort. Malmquist productivity measures a DMU's efficiency over time. This is due to the emerging development, procurement, and acquisition of the organization's business systems in this study. Simply, the organization has not had comprehensive in-country business systems until recently. Therefore, extracting the data was not available for thorough analysis before 2019. Network analysis is a multi-stage DEA application where the primary output results are reintroduced as the input variable in the second stage analysis (Zhu, 2014). Replicating best practices and activities of the organization that may be underperforming and inefficient are out of scope for this effort. This effort benchmarked the organization's efficiency and identified area(s) of improvement for the future.

There is a difference between for-profit and nonprofit organizations. For-profit organizations can evaluate net profits as a variable in DEA analysis. In contrast, nonprofits do not and may view donor requirements (e.g., the number of beneficiaries served) as a critical performance measure. A nonprofit performance and evaluation should include what good performance may resemble in a DEA evaluation. The assessment can become more complex when additional measures are added. To address this complexity, the aggregation of performance measures or metrics down to a singular performance measure is an acceptable alternative compared to for-profit organizations (Greenberg & Nunamaker, 1987).

Theoretical Framework

Efficiency generally assumes the minimum number of inputs with the maximum output.

- $Efficiency = Output/Input$

As prescribed in the humanitarian sector, performance meets a given project's objectives, goals, or targets. These are determined and agreed upon by the stakeholder (donors) and the implementing partner (INGOs). The concept for DEA was initially introduced by Farrell (1957).

Farrell identified a gap that captured the performance; however, it did not consider the efficiency of production based on the multiple inputs for production (Cooper, Seiford, et al., 2004). Later, Charnes et al. (1978) developed and constructed a linear programming model for frontier analysis and calculating the efficiency of DMUs in a frontier model. The model developed provides for an input orientation that assumes constant returns to scale or CRS. If the input variable changes (increased or decreased) in CRS, the output is predicted to have a proportional shift related to the input variable(s). The literature may refer to the CRS component as the CCR model named after Charnes et al. (1978), who developed the CRS technique for DEA.

Several other studies follow Charnes et al. (1978) that are important in the evolution of DEA development. Banker et al. (1984) introduced the variable returns to scale or VRS. In VRS, efficiency is an estimate that is not a proportional change, regardless of whether the inputs or outputs have increased or decreased (Cooper, Seiford, et al., 2011). The literature may refer to the VRS component as the BCC model named after Banker et al., who developed this technique.

The VRS (BCC) and CRS (CCR) models are the foundation for DEA. Since 1984, there have been many adaptions, and additional modeling techniques have emerged for DEA. The second approach of the DEA models is using the undesirable outputs as inputs (Hu & Wang, 2006; Zhou et al., 2017). The third DEA model uses the concept of weak disposability technology (Färe & Grosskopf, 2004; Mehdiloo & Podinovski, 2019; Zhou et al., 2017). In addition, discussion of slack, Malmquist, two-stage contextual, and many others have emerged to address the needs for academic and operational research and theoretical and practical perspectives in many industries.

Research Questions

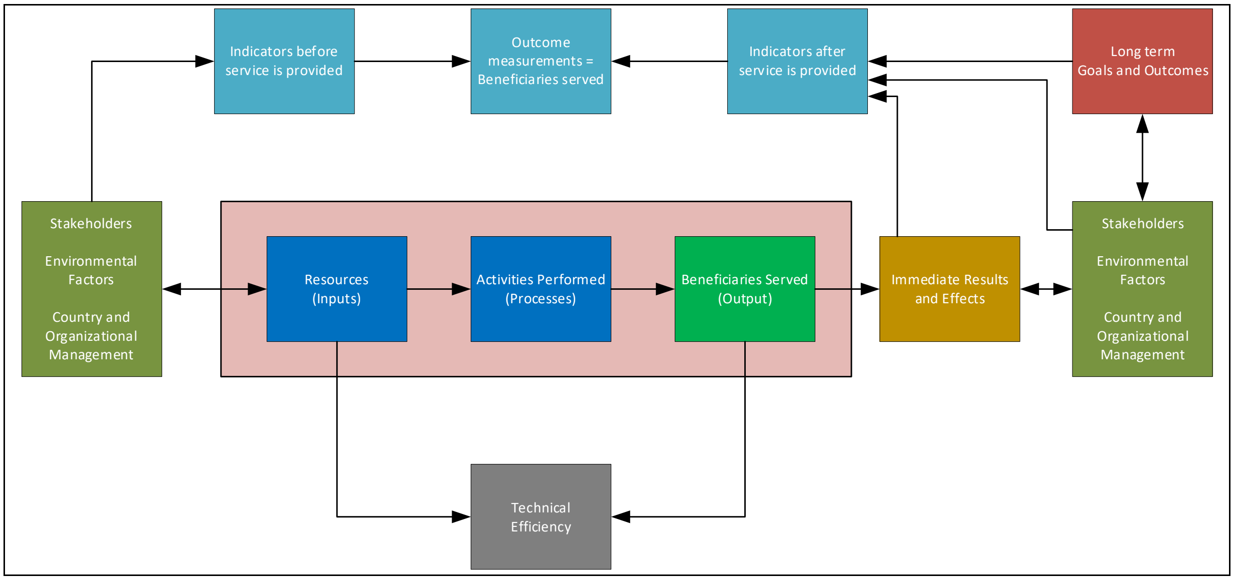
- RQ1. How do the DEA efficiency measures compare and evaluate the organization's country teams in the aggregate and within the organization's regional structure?
- RQ2. How do the DEA results of near peer efficiency compare to the organization's efficient vs. inefficient country teams?
- RQ3. What areas and level does DEA identify areas for improvement (slack and target values) within the organization's country operations?
- RQ4. Do the external variables of corruption and conflict change the efficiency scores of the organization's country teams?
- RQ5. What are the potential limitations of performing DEA analysis on humanitarian aid programs and organizations?

Humanitarian Operational Construct

Figure 2 is an adaptation of Sink and Tuttle's (1989) service organization model. I added the DEA to evaluate performance and the standard practice of indicator performance results in this construct. This depicts the organization's performance-oriented approach at a high level.

Figure 2

Performance Measurement Model for Service Organizations

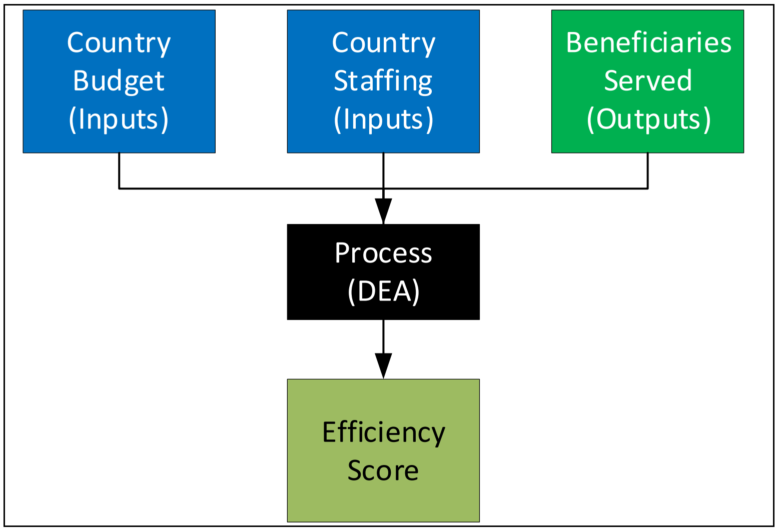


Note. Adapted to illustrate organizational performance construct. Adapted from "Planning and Measurement in Your Organization of the Future," by D. S. Sink and T. C. Tuttle, 1989. Copyright 1989 by Industrial Engineering and Management Press. Adapted with permission.

This study took the inputs (resources) and output (beneficiaries served) to determine the technical efficiency of each country's portfolio. Figure 3 is the study construct to collect and evaluate the inputs and outputs of the organization. The factors for Phase I was the budget and staffing data as inputs. The output was the number of beneficiaries served by each country's mission within the organization. In Phase II, the variables remained the same. The countries are separated based on their regional affiliation (Middle East, West Africa, and East Africa/Asia). Phase III added the external variables into the model to determine efficiency and factors that impact the respective country operations.

Figure 3

DEA Study Construct



Key Definitions

Balanced benchmarking: Balanced benchmarking is a technique that provides organizations and their management team(s) to assess and identify the effectiveness of different branches or units. The method enables companies to locate best practices that may not be observable using standard management tools or applications. Additionally, an organization can benchmark these areas to observe over time (Sherman & Zhu, 2013). Balanced benchmarking can be incorporated into traditional balanced scorecards that have been historically used in the commercial and private sectors or applied separately. For this study, balanced benchmarking refers to DEA.

Beneficiaries (output variable): This variable was the total number of beneficiaries who received support or services from the organization from a particular country team. This variable was an output variable and was often reported periodically to the various grant donors, determined by each grant agreement. In addition, this metric was reported by the organization's Monitoring, Evaluation, Accountability, and Learning (MEAL) department.

Budget (input variable - discretionary): The budget variable was the direct costs for each country's programming portfolio. The budget was the total operational costs for each country's portfolio. This includes procurement, operations and maintenance, and staff costs. The organization's finance department reported the budget variable.

Conflict (input variable – nondiscretionary): Conflict has a negative impact on the ability of humanitarian aid organizations to perform relief efforts when there is conflict. The spectrum or level of conflict can be an obstacle for NGOs in conflict zones. Humanitarian organizations require access to these areas to provide aid and support to the affected populations in these areas. Conflict areas hinder and restrict access to these areas. The University of Gothenburg (2021) produces the conflict index. The conflict indexes were sourced from the Quality of Government Standard Dataset and are current as of 2020. The conflict index is on a scale from 1 to 10. Thus, one represents no conflict, and ten portray country conflict or conventional warfare in 2020 (Teorell et al., 2021). The conflict variable was necessary to evaluate the DEA analysis with this nondiscretionary variable to affect the efficiency scores of the countries in this study.

Constant Returns to Scale (CRS): CRS is a type of frontier model that can have an input or output orientation. It is assumed that if the input is increased or decreased, the output variable is estimated to change proportionally based on the input(s) changes (Cooper, Seiford, et al., 2011). In some cases, the term CCR is used to describe this model. CCR is derived from Charnes et al. (1978), who developed this DEA framework.

Corruption (input variable nondiscretionary): The corruption perception index (CPI) indicates a level of corruption in the public sector. The CPI assessment captures, at some level, the indicators of “bribery, diversion of public funding, use of public office for private gain, nepotism, and state capture” (Transparency International, 2021, para. 8). The derivative effects for INGOs that operate in low-scoring countries are the potential for additional internal process mechanisms that protect an organization from these corruption characteristics. These additional mechanisms would be an added cost and internal controls leveraged on a country program team to conduct and implement humanitarian aid operations.

Transparency International produces a corruption perception index (CPI) each calendar year. The CPI aggregates data from many different sources that provide business and country experts on the perceived level of corruption. For calendar 2020, the CPI applied up to thirteen various data sources[1]. The CPI ranks countries from 0-100. A ranking of zero is the highest level of corruption. A 100 is perceived as the lowest level of corruption. For 2020, the CPI rankings were from 88 (low corruption) to 12 (high corruption).

Effectiveness: Effectiveness is the degree to which goals and outcomes are achieved. This assumes that the correct evidence of services or interventions has been collected and measured. (Papanicolas & Smith, 2013; Scott, 2014).

Efficiency: Efficiency focuses on a systems-level understanding how resources are utilized to meet the objectives of a given programmatic system (Papanicolas & Smith, 2013). The term efficiency uses the least amount of inputs to maximize output. Efficiency requires the reduction in the use of unnecessary resources that are used to produce a given output (Banton, 2020). Efficiency is a measurable concept that can be expressed by a ratio or percentage.

- Efficiency = Output ÷ Input

[1] Description of the data sources used for CPI index for calendar year 2020 can be found at https://images.transparencycdn.org/images/CPI_20_SourceDescription_EN.pdf

Efficiency is an important concept because all resources (inputs) are often limited resources (e.g., money, time, people, materials; Banton, 2020). In DEA terms, efficiency can be described in the following three terms. “1) A DMU may increase the output without increasing its input. 2) Reduce its input without reducing its output. 3) Reduce its input while increasing its output” (Simar et al., 2012, p. 853).

In this study, efficiency was measured using the DEA methodology. A 1.00 efficiency score demonstrates that an organizational unit (Decision Making Unit [DMU]) is efficient. An efficiency score less that 1.00 (< 1.00) is determined to be inefficient in comparison to other homogeneous DMUs.

Linear programing: Linear programming is a mathematical modeling technique where a linear function is minimized or maximized based on the various constraints. Linear programming techniques support quantitative decisions in business planning, operational research, and industrial engineering (Gregersen, 2017).

Performance: Performance is meeting the objectives or targets for a given project (Abdel-Kader & Wadongo, 2011). The performance of an organization is determined by the stakeholders, internal or external, in correspondence with the goals that reflect the values of an organization. Examples of stakeholders can be regulators, management, beneficiaries, or employees (Shaw, 2003).

Performance evaluation: Performance evaluation is the evaluation of the various performance measurements on a holistic level. Performance evaluation can be viewed as a continuous improvement tool or benchmarking. In addition, performance evaluation can identify best practices or processes, identify strengths, weaknesses, and opportunities, and prepare an organization to meet customers or other requirements of an organization (Zhu, 2014).

Performance measurement: Performance management is collecting, analyzing, and reporting the performance of a department or individuals of an organization. Performance measurement provides a status of an organization's implementation of a current strategy (Shaw, 2003).

Personnel (input variable - discretionary): Personnel consists of the number of employees, consultants, and volunteers who provided administrative support and program implementation at the country level. This variable is an average of the number of employees over the calendar year 2020 period. This variable was reported from the organization's Human Resources department.

Variable Returns to Scale (VRS): Variable returns to scale (VRS) is a frontier scale used in data envelopment analysis (DEA). This assists in determining an estimate of the efficiencies. There should not be a proportional change based on the increase or decrease of the inputs or outputs (Cooper, Seiford, et al., 2011; Majumder & Chetty, 2017). In some cases, the term BCC is used to describe this model. BCC is derived from the Banker et al. (1984), who developed this DEA framework.

Significance of Proposed Research

Although there are multiple examples from many different industries (banking, health care, supply chain, and others), there is a gap in applying DEA for the humanitarian sector and NGOs in general. The examples above are discussed in Chapter 2. Donors have an expectation that INGOs meet their stated goals and make the best use of the resources provided - to improve the efficiency of the funds provided to the NGO or implementing partner of the grant(s). INGOs can make use of DEA as a tool to better their performance and identify best practices within their respective organizations. It can demonstrate the utility of DEA for both the INGO and donor organizations. Additionally, there is potential for government and donor oversight beyond the reporting requirements currently stipulated in the grants dispersed through their respective agencies.

Positionality

I am currently an employee of the organization and a business analyst with access to business data. This research effort is to demonstrate the utility of DEA for humanitarian aid organizations. Although DEA has not been widely used, it is believed that this will provide humanitarian aid organizations and donors with an additional application to measure performance beyond the current concepts used today. I have both a professional and personal interest in conducting this study. I am a Ph.D. student attending Pepperdine University, located in Los Angeles, CA.

I do not have any financial or other interests in this endeavor's software applications. The software used was selected based on familiarity and use from previous practical statistical, DEA applications, and qualitative studies in my academic, research, and professional responsibilities.

Summary

As discussed in this chapter, donor institutions and governments will continue to scrutinize the performance of INGOs. The humanitarian sector's competitive nature and the finite amount of donor funding necessitate a different way to find more efficient and effective ways to utilize those resources. Historically, grants have required soft outcomes regarding performance and efficiency. However, given donors' behavior in more recent years of tracking performance metrics, their intentions are becoming more contract-like and transactional in their behavior.

It becomes more critical for INGOs to meet the performance criteria as outlined in a grant agreement and find ways to become more efficient with the resources provided through donor funds. INGOs must be able to adapt to this new paradigm. An example of the additional oversight and paradigm shift was Spain's Agency for International Cooperation for Development. The Spanish agency reviewed the efficiency of forty-eight humanitarian projects from 2001-2006. The Spanish agency used DEA to evaluate these programs from an efficiency perspective (Martin-Perez & Martin-Cruz, 2017). Donor institutions have the required information at their discretion to use DEA. Donors collect data through monthly programmatic reports and annual audits from the INGOs during the grant's lifecycle.

Alda and Cuesta (2019) provided a compelling argument that the humanitarian sector should use DEA to measure the efficiency of their operations. A primary imperative for humanitarian organizations is saving lives and preventing hunger, disease, and poverty. Therefore, a more efficient means to measure the performance and use of donor funding necessitate DEA as a practical evaluation tool.

DEA should be viewed as an analytical tool, no different from a balanced scorecard, balance sheet, or another management device. The difference is how DEA can be used to identify the areas that are or are not performing efficiently. DEA can reduce the intuition factor where decisions are made objectively.

Many industries have utilized DEA over the years. But DEA use appears to be rare in the humanitarian arena. This is a cultural and mindset change for the future. One should consider previous changes in the cultural perspective in humanitarian operations (i.e., project management, another discipline used to enhance performance in an organization). Previously, many organizations were reluctant to adopt a project or program management culture. INGOs are no different. Many have viewed program management as creating more internal bureaucracy (Vincent-Smith, 2016). However, INGOs that have embraced program management have seen an increase in performance. Projects are completed on time and within budget (Vincent-Smith, 2016). Médecins Sans Frontières (MSF), also known as Doctors Without Borders, Save the Children, and other NGOs, instituted program management at their headquarters and field locations. Forging a program management mindset has increased performance in these organizations and has aligned costs and resources across many functional areas (Vincent-Smith, 2016). From a program management perspective, implementing DEA should be viewed as the next logical step for improving performance and promoting the efficient use of the resources provided to INGOs.

Chapter 2 discusses government donors' actions on INGOs through statutes, policies, and regulations. Government donors provide oversight of their respective regulations through reporting mechanisms and audits. Additionally, I discuss nonprofit management perspectives using results-based management, human resources applying several reform initiatives, strategic planning efforts, and views of donor oversight through their audit mechanisms. Lastly, I discuss the Data Envelopment Analysis. Specifically, how DEA came to fruition, understanding the CRS and VRS models, DEA concepts, the variables for this study. I address potential DEA applications of the PIM DEA software and how INGO management can incorporate DEA results into balance scorecard approaches to monitor and report DEA efficiency within and INGOs organizational structure.

Chapter 2. Literature Review

This chapter reviews shifting government actions and nonprofits to become more efficient. Second is a discussion of and background on Data Envelopment Analysis (DEA) and its potential uses in the humanitarian sector. Anecdotes are used throughout this chapter to demonstrate DEA utility in the various commercial sectors and its possible benefits for humanitarian organizations. Lastly, there is a discussion of the multiple variables and data sets used in this study.

Government Donors

For decades, national governments and international agencies have relied on INGOs and outsourced humanitarian efforts to them. However, within the last 20 years, efficient use of donor resources has become more of a priority, if not an imperative, for nongovernmental organizations (Martin-Perez & Martin-Cruz, 2017). Governments have strived for process improvements and efficiency over the years. This is not a new phenomenon. During the Clinton administration from 1993–2001, the Government Performance and Results Act (GPRA, 1993) was enacted to improve government performance. During the same period, Vice President Al Gore spearheaded the reinventing of the merit system, promoting efficiency in the government workplace (Light, 2000). The GRPA had five main areas for government accountability:

- Establish goals for all government agencies
- Aid Congressional committees in their ability to amend, suspend, or establish programs based on performance for each fiscal year.
- Improve performance for all agencies and measure their effectiveness.
- Highlight operational processes, skills technology, human capital information, and other resources needed to meet new goals for that fiscal year.

- Compare current results to previous years as a measure of effectiveness. (Medina-Borja, 2002)

The GRPA (1993) was enacted forcing the U.S. federal government to become more performance- and efficiency-oriented. GRPA mandated several actions to improve the government's efforts in both policy and practice. U.S. government agencies were required to create strategic plans, identify key performance measures and objectives, and report on the activities of these measures to the U.S. Congress. The Office of Management and Budget (OMB) would oversee and coordinate reporting on these activities and measures to the president and Congress annually (GRPA, 1993).

Later in 2010, Congress and the Obama administration revised and updated the GRPA of 1993 (GRPA, 2010). This updated GRPA, still reporting to OMB, further codified the rules for strategic planning efforts and placed limitations on the number of pilot programs for federal agencies and performance grading for federal agencies (GRPA, 2010).

The Government Accounting Office (GAO) provides Congress with additional oversight to report on the performance of the executive agencies. The GAO's efforts are to improve government efficiency and identify where the potential of taxpayer dollars are not utilized productively and where waste of taxpayer dollars is occurring (GAO, 2021). Dating back to the mid-1990s and up to the present, the GAO has identified several areas to improve USAID management of overseas grants. For example, in December of 2020, the GAO provided recommendations to USAID to improve the timeliness of aid analysis and expenditures of grants managed by USAID (GAO, 2021). To illustrate this challenge, one only needs to review the humanitarian response to the Haiti earthquake in 2010. There were three significant challenges to the Haiti humanitarian aid effort and donor spending: accountability, coordination, and effectiveness (VanRooyen, 2013). While accountability and coordination alone were enormously difficult, effectiveness was even more problematic – data was not tracked or collected (VanRooyen, 2013). At the time, the focus was to send financial support and spend the monies provided. The question years after the effort was, what impact did those funds have on the overall humanitarian effort?

The GAO reviewed the disbursement of U.S. funding since the Haiti earthquake in 2010. In 2015, the GAO reported mixed results from many programs sponsored by USAID. After ten years, U.S. Congressional supplemental funding is still ongoing. This is not uncommon for multi-year projects in complex environments; however, this illustrates the need to monitor aid programs' performance and effectiveness in general with the expectation of tangible results.

Under the Trump Administration, the Code of Federal Regulations (CFR) Title 2 Part 200 was updated and modified. CFR 2 Part 200 is specific to organizations that receive grants from the U.S. government. The revisions and updates to the CFR occur every five years. The OMB is responsible for coordinating various government agencies and external nonprofit entities. However, these recent updates have the potential to be game changers within the nonprofit arena. Grants that previously expected soft results from grant recipients had shifted the paradigm to a more results-oriented focus. Under this new paradigm, a humanitarian effort like Haiti would focus on financial and result-oriented performance. Federal agencies that provide grants must now monitor the performance results as stipulated in the grant agreement. Both financial and performance metrics are currently being monitored.

Several changes have occurred since CFR 2 Part 200 was adopted and implemented. The following discussion affects INGOs' program implementation and administrative concerns. This discussion addresses No Cost Extensions (NCE), Negotiated Indirect Cost Rate Agreement (NICRA), and communications policies and technologies.

No cost extensions (NCE) are a tool used by aid organizations to extend the period of performance of a particular grant because the aid organization has not finished spending the allocated funds, despite the performance period coming to an end. CFR 2 Part 200 (2020) now stipulates that an NCE can be requested only once and cannot be based on unobligated funds. The unspent funds must be based on other factors that would have disrupted the program being implemented. Examples could include various dynamic factors (e.g., an outbreak in hostilities between two sovereign nations, an insurgency that would have curtailed access to a particular part of a country, or, more recently, nationwide lockdown and travel restrictions due to COVID-19). Aid organizations must request the NCE no later than 45 days before the end of the performance period. This requires a higher level of monitoring of program management and financial reporting by both the U.S. government agency and the aid organization than in previous years.

Complicating the accounting of grant spending is the overhead cost, commonly referred to as the Negotiated Indirect Cost Rate Agreement (NICRA). The NICRA costs are indirect costs that have been negotiated between an aid organization and the U.S. government. The NICRA is a specified percentage of the overall program costs to support the administrative management of a grant program. The NICRA was once considered proprietary information for an aid organization. However, the NICRA indirect costs percentages are to be published by the U.S. government agency in the future for transparency purposes (United States Office of Management and Budget, 2020). For the purposes of this study, the NICRA will be omitted from the budget variable. Indirect costs rates can vary among donors. The budget variable will be actual direct costs associated with each country or DMU. Adding the NICRA may skew the outcome of the DEA models.

The Bureau of Humanitarian Affairs (BHA) under USAID has established a standardized list of 199 indicators to measure performance. This list is also standard among United Nations, European Union, United Kingdom, and other donor entities. This list includes the areas that an aid organization will identify for performance tracking purposes and, more importantly, the metrics on which an organization is critiqued. In the future, both financial spending and performance will be graded (United States Office of Management and Budget, 2020).

Other areas influencing performance metrics are driven by law and public policy. The John S. McCain National Defense Authorization Act for Fiscal Year 2019 (2018) prohibits the procurement or contracting of specific communications technologies. These are specific to Chinese-related communications and technologies companies. CFR 2 Part 200 (2020) follows this statute and prohibits the use of U.S. grant funds for contracting or purchasing these types of technologies. Communication is difficult in many areas where INGOs operate due to the lack of internet infrastructure to support data transmission for functional areas, including finance, human resources, program implementation, logistics, monitoring and evaluation, and others. Chinese communications technologies have a robust presence in many regions where INGOs operate. This will force many INGOs that accept U.S. donor grants to source their communication infrastructure from companies other than China. To further reinforce this concept, President Biden, in his speech to Congress in his first 100 days, emphasized the importance of U.S. tax dollars being used to buy U.S.-made products (Biden, 2021).

The United States is not alone in providing oversight and awareness of government funds that support humanitarian aid. In 2019, a report from the Comptroller and Auditor General of the

U.K. discussed humanitarian aid and development (National Audit Office, 2019). The report addresses many program performance, effectiveness, and oversight issues. For example, the report had noted that the UK government had not monitored the effectiveness of program expenditures. However, at the departmental level, monitoring of humanitarian aid was being conducted after a given program. As a result, in 2019, the U.K. departments started developing a framework to better program oversight and effectiveness (National Audit Office, 2019). The frameworks are intended to establish target goals and evaluate humanitarian aid's inputs, activities, and outputs. However, this new framework does not assess the impact or value of the money expended on various humanitarian aid projects (National Audit Office, 2019).

The United States, the UK, and the EU have begun to stipulate rules to aid organizations that enhance the policies of nation-state donors or regional agreements. The European Union mandates adherence to the General Data Protection Regulation (GDPR, 2016). Simply, if an INGO accepts donor funds from the European Union or a member state, the telecommunications and data activities would fall under the auspices of the GDPR extraterritorial application (GDPR, 2016) as a matter of policy. Many countries where INGOs operate have adopted GDPR-like regulations. For example, in Africa, 31 countries have constitutionally or legislatively adopted data protection policies (Greenleaf & Cottier, 2020). The African Union developed a data protection agreement in 2014, however, it has yet to be ratified by the remainder of African member states (Deloitte, 2017). In the Middle East, 50% of Gulf Cooperation Council states have or are developing data protection policies (Global Systems Mobile Association, 2019). It is expected that many other countries will continue to adopt similar GDPR regulations in the future.

Donors – Oversight – Audits

The European Union (EU), United Kingdom, and other governments are taking similar steps to require better performance from the nonprofit and NGO organizations. Annual audits of humanitarian aid programs are now becoming the norm from the UN, EU, UK, and other government entities, seeking to make INGOs better stewards of the funding resources provided to them.

As discussed in Chapter 1, Spain's Agency for International Cooperation for Development analyzed forty-eight projects implemented from 2001–2006. The projects were in Morocco and Mozambique. The Spanish agency utilized Data Envelopment Analysis specifically to evaluate the aid projects in these countries for the efficiency of the provided donor resources. The assistance provided to NGOs was to promote development and welfare assistance in these countries (Martin-Perez & Martin-Cruz, 2017). The output orientation was utilized in the Spanish agency example because of the specified resource level (e.g., budget). The aid effort was focused on the number of individuals reached for a given program (Martin-Perez & Martin-Cruz, 2017). In this case, the literature suggests that of the 48 programs reviewed, 25% (12) were efficient compared to all aid programs in this study (Martin-Perez & Martin-Cruz, 2017). Moreover, Morocco had 26.6% (8), and Mozambique with 22.4% (4) programs that were efficient using DEA analysis (Martin-Perez & Martin-Cruz, 2017).

The U.S. government, EU, UN, and other international agencies conduct annual audits of programs implemented by INGOs. These donors and their organizations themselves use the audits to determine how well the monies are utilized. Governments that provide donor funds to international organizations have begun to pressure the international community to be even more accountable. Government donors expect that their contributions are used effectively and efficiently (Monfardini & Maravic, 2019). An "audit society" has been created over the last 20 years (Monfardini & Maravic, 2019, p. 143). The audit efforts in the past have focused on the financials, but over time are being broadened to include other operational oversight areas. This audit behavior by donor organizations can be traced back to 2000.

The Meltzer Commission was established by Congress in 1998 and tasked to identify future policies toward the World Bank, International Monetary Fund, the United Nations, and other regional international organizations (Monfardini & Maravic, 2019). The Metzler Commission had stated that "there is a wide gap between the World Banks rhetoric and promises and their performance and achievement" (Meltzer, 2000, p. 10). The Volker Commission focused on the Oil for Food Program (Volker et al., 2005; Christoff, 2005). The Volker report had stated, "the United Nations' observation mechanism suffered critical management failures that reduced the effectiveness of its monitoring capabilities" (Volker et al., 2005, p. 301). These commissions and other governments that contribute to international organizations require that their contributions are used effectively and efficiently. Governments conduct audits on international agencies; in turn, those agencies audit the INGOs.

Weak internal controls by INGOs can lead to fraud taking root and going undetected, preventing an INGO from operating effectively and efficiently (Feng, 2020). Audits and oversight of donor contributions and the efficient use of those resources may be a challenge for INGOs, but they too are not without risk. In the nonprofit literature, Petrovits et al. (2011) reported that an audit finding could lower the confidence of donors and curtail their providing future funding. Additionally, audit findings can make it more difficult for creditors to offer favorable credit terms to an INGO.

Scarce resources that are available for international cooperation and humanitarian aid have often focused on the delivery of aid itself. However, achieving this goal is no longer enough. Efficiency is now more of a priority in today's humanitarian sector. The challenge is controlling and managing the level of those scarce resources to maximize long-term efficiency and potentially make those dollars go further and do more (Martin-Perez & Martin- Cruz, 2017). This ultimately increases the pressure on INGOs, donors, and other stakeholders involved in humanitarian aid projects.

As discussed in Chapter 1, while governments and international agencies have outsourced humanitarian efforts for decades, it is only within more recent years that the efficiency of how INGOs implement those donor resources has come to the forefront (Martin-Perez & Martin-Cruz, 2017). Meantime, recent years have seen a decrease in financial and material assistance for humanitarian efforts. At the same time, there has been an increase in natural and man-made disasters. For these reasons, efficiency in delivering humanitarian aid is more crucial now more than ever (Harat et al., 2015).

Through an audit, benchmarking, or other management tool mechanisms, DEA can be applied to measure the performance and efficiency of an organization. The ability of an organization to meet its stated objectives and goals based on the resources hinges on whether the desired performance criteria (e.g., services and products, reach the beneficiaries for whom humanitarian aid is intended; Sherman, 1982). DEA could be employed to audit resource allocation and review the implementation of aid operations (Sherman, 1982). However, while DEA can address the efficiency of an organization's DMUs within a given data set, it should not be used to evaluate the effectiveness of an aid program.

DEA at the Proposal Stage

Audits are typically conducted post-implementation or at the conclusion of an aid project. Essentially, this is a lagging indicator or assessment of a program after its completion. As discussed in Chapter 1, there have been examples of how DEA could be used to select proposals for a humanitarian aid project at the outset. For instance, Partovi (2011) discussed how a company used DEA as part of the company's criteria to choose a STEM school for philanthropic support. Theoretically, the same concept could be applied to select an INGO to provide humanitarian aid. Before awarding grants, government and international agencies require proposal information, including budget narratives, personnel, procurement costs and supplies, program design, and beneficiary indicators or targets. These and other components could be used to determine the potential comparative efficiency of INGOs submitting proposals to the given organization. DEA could be used as an additional selection criterion in addition to already existing standards. Grants are advertised with a fixed ceiling or a not-to-exceed total value amount. The difference would be in the procurement, personnel, indirect/overhead cost percentage, and the expected number of beneficiaries served during the performance period. The donor organization would need to extract the data from these areas and perform a DEA analysis to derive a comparative efficiency score among the competing INGO organizations. The difference in this approach is that the donor organization preemptively conducts DEA during the selection process versus an audit after an aid program has concluded.

Table 1 illustrates how a donor organization may use DEA as a selection tool. The advertised grant assumes a maximum amount of $1 million in the example. Each INGO would provide its respective program's design, number of personnel, procurement costs, and the beneficiaries to be served. The NICRA percentages difference would be subtracted from the $1 million value of the grant, which would derive the direct costs for implementing the program. The procurement costs (X3) would be subtracted from the direct costs to derive the budget (X1) remainder of the available cost for personnel (X2) and other capital costs. Budget (X1), personnel (X2), and procurement (X3) are the input variables. The beneficiary (Y1) is the output variable. By applying DEA methodologies, utilizing CRS (input orientation) and VRS (output orientation), one can derive the efficiency levels in each case. In this example, DMU 3 and DMU 5 are comparatively efficient, with a CRS and VRS efficiency score of 1.00. DMU 1, DMU 2, and DMU 4 are deemed inefficient in this example. Table 1 illustrates how an evaluation of INGO proposals could be achieved with the example below.

Table 1

Notional Donor Selection for INGO Proposals

INGO	Grant	NICRA	Direct Costs	Budget (X1)	Personnel (X2)	Procurement (X3)	Beneficiary (Y1)	CRS Efficiency Score	VRS Efficiency Score
DMU1	$1,000,000	5%	$950,000	$570,000	150	$ 380,000	1700	0.77	0.85
DMU2	$1,000,000	10%	$900,000	$540,000	110	$ 360,000	1600	0.9	0.94
DMU3	$1,000,000	15%	$850,000	$510,000	140	$ 340,000	2000	1.00	1.00
DMU4	$1,000,000	20%	$800,000	$560,000	120	$ 240,000	1500	0.87	0.91
DMU5	$1,000,000	25%	$750,000	$525,000	100	$ 225,000	1600	1.00	1.00

As depicted in Table 1, a difference in the efficiency score depends on the model being used. This can also have slight variation if the model is specific to either model's input or output orientation. For example, in the notational depiction from Table 1, CRS was input-oriented, and VRS was output-oriented. In both cases above, DMU 3 and DMU 5 were both deemed technically efficient.

This approach is not without its challenges. The relevant criteria for DEA would be an internal decision within the donor organization to analyze and compare the INGOs' submitted proposal applications for a given grant. A common practice is for donors to advertise or make known the selection criteria. Another challenge may be the artificial inflation of beneficiary indicators or targets by the INGOs, which could skew the performance and comparative efficiency scores. An example can be found in the USAID/BHA (2020) adjustment of these indicators. The indicators and targets initially submitted in the INGO proposal are reviewed and adjusted after the first 90 days during the performance period. The revised indicators/targets are then reported to USAID/BHA. This is an opportunity for the INGO to provide refined targets or goals for a given program. The donors, in this case, USAID or BHA, are implying that the original grant targets may be inflated, underestimated, or in error based on previous assessments before implementing an aid program. This is a known challenge for both the donors and INGOs.

Nonprofit Reform

As previously discussed in the donor actions and activities, nonprofits and international NGOs have been pressured to make these changes and typically tend to follow and react to donor requirements rather than innovate new systems on their own. Compliance with these efforts is in the best interest of the INGOs. Not complying with donor mandates puts INGOs at risk for future funding at a time when a lack of funding, increased competition, and the pressure to perform are as pressing as ever.

Werther and Berman (2001) focused on the management of nonprofits at a high level. Their focus is on the development of an organization’s mission, value, and strategic planning efforts. Werther and Berman acknowledged the dynamic and challenging environment that INGOs must navigate. The focus for the authors is on management practices and human resources for the volatile environments where nonprofits operate. In addition, the authors addressed the critical aspect of fundraising donor contributions needed to facilitate strategic planning efforts.

Werther and Berman (2001) broke down the management echelon into three levels: board of directors, strategic, and operational. Managers at all levels must organize their resources and identify the organization's objectives from the highest level down to the operational levels. The key to managing the resources and objectives is the development of a strategic plan moving forward.

Another area that Werther and Berman (2001) focused on is human resources and the evaluation methodologies. The environments where INGOs operate are complex and challenging, and programs are labor-intensive. Therefore, program implementation and evaluation are often central to meeting donor requirements and reporting an INGO’s accomplishments. Training the staff ensures that aid programs are implemented with an organization’s project management procedures, procurement, financial management, and evaluation processes and procedures.

Program performance, evaluation, and results can be in conflict when comparing performance and effectiveness. “Effectiveness or efficiency may be sacrificed for performance” (Werther & Berman, 2001, p. 117). This is due to the criteria for performance results based on the donor requirements in the grant agreements. Performance can take priority over effectiveness and efficiency because the donor requirements are central to many grant agreements. In contrast, effectiveness or efficiency is not.

Defining organizational effectiveness has been a challenge for each INGO and the sector in general (Scott, 2014). Pressures to reform have been a challenge at every level, from the donor to the local level where programs are implemented. Light (2000) described several areas for reform in the nonprofit sector. Most notable are the discussions on scientific management, war on waste, and watchful eyes (Frederickson, 2003; Light 2000). Scientific management is the organizational management theory to enhance efficiency and organizational effectiveness. Scientific management complies with rule sets and internal controls to deliver the services of a program. This is accountability rather than a performance measure.

The war on waste is to contain costs and process reengineering for implementing programs. The war on waste focuses on staff and the organization to implement programs with necessary supplies and personnel. There is a linkage to be made between the war on waste and performance. Personnel training/investment and process improvement are methods for tackling waste. And the war on waste can root out inefficiencies, fraud, and abuse in an organization. (Light, 2000).

The concept of watchful eyes relates to the oversight of the donors and transparency. The premise is that nonprofits and INGOs will not act unethically when closely monitored. This is done through various avenues. Donors require periodic reporting of activities, costs, and performance. In the U.S., the Internal Revenue Service requires nonprofits that meet rule 501(c) status to submit Form 990 at the end of the organization's tax year. Elements of Form 990 provide the public with an overview of the financial standing, mission, organizational accomplishments, board makeup, and salaries of company officers, among other considerations. Donor audits provide an in-depth review of financial, internal controls, monitoring, and best practices.

Results-based management has been utilized in both the profit and nonprofit sectors for the last couple of decades. Results-based management emphasizes performance and achievements (e.g., outputs, outcomes, and impacts; Kakaletri & Ntomis, 2017). A results-based management approach focuses on the resources and efforts with the intended results as the end state of a humanitarian aid program. Humanitarian organizations capture this philosophy in the logical framework, also known as a log frame. The logical framework captures the activities, outputs, outcomes, and goals. Each is associated with the previous stages are program summary, indicators, means of verification, and their associated risks or assumptions. See Table 2 as a notional template of a logical framework.

Table 2

Logical Framework (Log Frame)

	Project Summary	Indicators	Means of Verifications	Risk/Assumptions
Goal				
Outcome				
Output				
Activities				

Note: Bullen (2021). Adapted from *How to Write a Logical Framework (LogFrame)*. (https://tools4dev.org/resources/how-to-write-a-logical-framework-logframe/). In the Public domain.

The logical framework genesis became prevalent in the early 1970s by USAID. The intent of the logical framework was to be used as a "formal and neutral instrument" to evaluate USAID programs (Martinez & Cooper, 2020, p. 1241). The logical framework is a 4 x 4 matrix and is a critical artifact that encapsulates how the INGO will address the given aid program. The purpose of the logical framework is to reduce the complexities of a program down to the essence of a humanitarian aid project. The logical framework attempts to establish the intervention priorities and measure the work of the INGO while simultaneously depoliticizing the efforts.

Some would argue that the logical framework oversimplifies humanitarian programs' social and political environments (Gasper, 2020; Martinez & Cooper, 2020).

The log frame is an "If, "And," "Then" proposition for an organization to summarize how it plans to achieve the desired results conceptually and for the donor to review and visualize. The logical framework can begin with the activities row moving across and completing the relevant information for the project summary, indicators, verification, and risk/assumptions pertaining to the activities. "If" begins with the project summary, "And" ends with the Risk/Assumption columns. "Then" repeats the cycle for the Output row and the following areas. Figure 4 is an example.

Figure 4

Logical Framework (If, And, Then Information Flow)

	Project Summary	Indicators	Means of Verifications	Risk/Assumptions
Goal				
Outcome				
Output	THEN			
Activities	IF			AND

Note: Bullen (2021). Adapted from *How to Write a Logical Framework (LogFrame)*. (https://tools4dev.org/resources/how-to-write-a-logical-framework-logframe/). In the Public domain.

Given the financial constraints, the environment where INGOs operate, and the mounting pressure of accountability, results-based management philosophies have become more important and prevalent in the humanitarian sector. This philosophical perspective is used to align management and employees towards a given humanitarian assistance program (Kakaletri & Ntomis, 2017).

Scientific and results-based management theories are not new. This philosophy can be traced back to the management philosophy of former Secretary of Defense Robert MacNamara in the U.S. government Planning, Programming, Budgeting, and Execution (PPBE) cycle from the 1960s (Martinez & Cooper, 2020). Later, it was used in GRPA and Vice President Gore's merit initiatives (Light, 2000; Martinez & Cooper, 2020). The focus on strategic planning, accountability, budgeting, and performance impacted the government donor space to other agencies and government institutions. The PPBE, GRPA, and merit initiatives have informed the government administration and government donors. Over time, the logical framework has been passed down to INGOs and other funding agencies. However, this connection between governments, the INGOs, and the use of the logical framework promotes a rationale for bureaucracies (Martinez & Cooper, 2020). Nonprofits and INGOs are compelled to adhere to these principles in the past and present. However, these efforts often reflect the results or performance at the detriment of efficiency and maximizing the resource to substantiate results.

Data Envelopment Analysis

Data Envelopment Analysis (DEA) was developed to evaluate the comparative efficiencies of departments and organizational units. These units can consist of bank branches, transportation and logistics companies, hospital departments, schools, and universities, to name a few. The DEA methodology is directed toward frontiers instead of central statistical tendencies (Cooper, Seiford, et al., 2011). Because of this distinction, DEA can be more effective in discovering relationships than other quantitative or qualitative methodologies. The critical factor in DEA for each area previously described is the comparative assessment for each organizational department. DEA assesses the same functional areas or resources they used and their output (Thanassoulis, 2001). Thus, DEA makes it possible to compare the operating units of output levels relative to their input levels. The assessed efficiency of a given unit reflects resource conservation compared to the unit's output.

Conversely, one analyzes the outputs without providing additional resources (Emrouznejad & Thanassoulis, 2020, 2021). It is also important to note that DEA is not an absolute measure of efficiency. However, the practitioner can make assumptions when comparing the number of inputs and outputs concerning other DMUs within the organization. By making these assumptions, DEA can identify a DMU's performance relative to the other DMUs within the organizational construct (Thanassoulis, 2001). In practice, DEA can go beyond the measure of efficiency. DEA can provide additional insights to understand the operating practices, multiple resources, and their allocations, scale, and size to improve a functional unit's performance (Emrouznejad & Thanassoulis, 2021).

The genesis of Data Envelopment Analysis was prompted by Farrell in 1957 (Cooper et al., 2004). Farrell was interested in developing a methodology for evaluating productivity. The challenge was to formulate a measurement that incorporated many inputs to determine a measurement for productivity. However, combining multiple inputs was constrained and failed to produce a viable means to measure efficiency. Therefore, Farrell proposed an activity-based approach to combine various input and output elements to address this challenge. Although Farrell was primarily focused on productivity, it became more apparent that the measure was changing to efficiency (Cooper et al., 2004).

Later, Charnes et al. (1978) developed the Data Envelopment Analysis methodology (DEA). DEA is a methodology that uses linear programming to evaluate the performance of organizational Decision Making Units (DMUs; Charnes et al., 1978). DMUs are the reference points for the organizational entities. DMUs can range from a corporate, departmental, or single entity for relative comparison using a DEA methodology. DEA compares each DMU with the multiple input and output variables as performance measures among the other DMUs. DEA measures multiple inputs and outputs from various performance measures to establish an efficiency frontier. The efficiency frontier is established through DEA based on each DMU's practices. DEA assigns an efficiency score or level to other DMUs based on the efficiency frontier compared to all other DMUs (Zhou et al., 2017). As previously described in Chapter 1, an efficient DMU will receive a score of 1.00. DMUs that are less than 1.00 (< 1.00) are considered inefficient in relation to those DMUs with a score of 1.00.

Since its inception in 1978, DEA has been modified to address the different requirements of organizational and operational research (Zhou et al., 2017). The primary DEA applications for this study will be employing the CRS and VRS techniques. However, many types of adaptations and modifications have enhanced DEA's utility over the years.

In the last 40 years, the interest in Data Envelopment Analysis has grown. From 1978 to 2016, approximately 10,300 journal articles discuss DEA (Emrouznejad & Yang, 2018). From 1978 to 2003, DEA was the subject of only 200 articles each year, primarily from 2000 to 2003. But interest in DEA has grown exponentially since 2003. More recently, from 2014 to 2016, over one thousand articles were published each year (Emrouznejad & Yang, 2018). That trend continues to the present, with an average of 1,262 journal articles on DEA over the last four years (Emrouznejad & Thanassoulis, 2020).

Much of the focus in the literature has been on DEA and DEA modeling. However, other articles have addressed myriad topics around benchmarking, operational research, energy efficiency, and performance evaluation. As discussed previously, DEA has been used in various sectors, including banking, energy, education, health, public policy, and other sectors. In addition, there has been a shift to applying DEA principles to energy efficiency, carbon dioxide emissions, and environmental protection (Emrouznejad & Yang, 2018; Zhou et al., 2018).

Although many commercial sectors have used DEA, there is a noticeable information gap in the humanitarian sector. To the present, the use of DEA in the aid and humanitarian sector is "scant" (Martin-Perez & Martin-Cruz, 2017, p. 5). As discussed previously in this chapter, a linkage in the public policy area can be made where government grants are used to fund INGOs. Financial and performance criteria are currently the norm for these grants. The next logical step would be to incorporate an efficiency score to evaluate INGOs' implementation of those grants provided by the governments, regional and international organizations.

The number of journal articles regarding DEA is testimony to its strength and applicability (Cook et al., 2013). In addition, DEA as a model, empirical orientation, and minimal a priori assumptions make DEA methodology an excellent application to determine the aid organizations' efficiency and the funding received. Prior specifications are not required in using basic DEA models for input and output estimates to determine efficiency (Asmild et al., 2007).

Mathematical Models

Before discussing the CCR and BCC models, an outline is required to define the mathematical notations discussed in the CCR and BCC models. This is only to describe the theoretical equations used in this study. There are many other mathematical equations used in DEA. However, this study is focused on the CCR and BCC models to derive the efficiency of the organization's country performance and efficiency. In Table 3 are the mathematical symbols used in the DEA formulas.

Table 3

Mathematical Notations for DEA

n	Number of DMUs
T	Number of inputs
M	Number of outputs
y_{rj}	Amount of output r produced by DMU_j
x_{ij}	Amount of input i produced by DMU_j
v_i	Weight given to input i
u_r	Weight given to output r
e	Constant/ Euler's number 2.718281828…
λ	Unit with the largest peer weight
λ_j	Weight given to DMUj
θ	Efficiency score of a DMU
Ɛ	A small positive number
∑	Summation of all values
s	Slack minimum (-) or maximum (+)
∀	For all

CCR/CRS Model

As previously discussed, CCR was developed by Charnes et al. (1978). It is important to note that CCR is proportional when evaluating the efficiency frontier for inputs and outputs. One can assume that there are a number DMUs to be assessed. Each DMU consumes differing numbers of inputs to produce a different number of outputs. The CRS model examines the reduction of the input variables while maintaining the output. The technical efficiency for DMU_j assumes that maximum efficiency is obtained for unit j, subject to all other units having a technical efficiency ≤ 1.

There are n DMUs that utilize m inputs to produce s outputs. Second, DMUj consumes x_{ij} of inputs for i and produces y_{rj} outputs for r. We can assume that $x_{ij} \geq 0$, and $y_{rj} \geq 0$, which means that each DMU has at a minimum of one positive input and output value. Charnes et al. (1978) provided this as a ratio, where DMU_j

= DMU_0 to evaluate all ratios of j =1, 2, 3…n DMU_j.. (Cooper, Seiford, et al., 2011, p.7)

Figure 5 depicts the CCR/CRS equation (Cooper, Seiford, et al., 2011, p. 8).

Figure 5

CCR/CRS Equation

$$\max h_o(u,v) = \frac{\sum_r u_r y_{ro}}{\sum_i v_i x_{io}} \tag{1.2}$$

subject to

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leq 1 \text{ for } j = 1, \ldots, n,$$

$$u_r, v_i \geq 0 \text{ for all } i \text{ and } r.$$

Note. Adapted from *Handbook on Data Envelopment Analysis* (p. 8), by W. W Cooper, H. Deng, L. Seiford, and J. Zhu. (2011). Springer (https://doi.org/10.1007/978-1-4419-6151-8_1). Copyright 2011 by Springer. Adapted with permission.

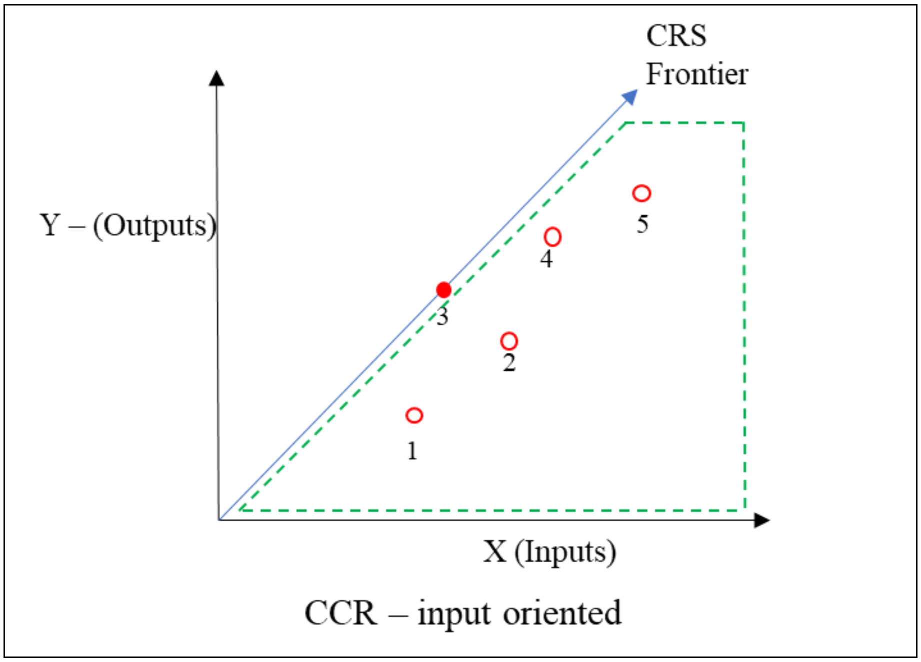
Where

- Technical efficiency = Max h_0 (u, v)
- y_{rj} is the output from r to unit j
- x_{ij} is the input of i to unit j
- u_r is the weight given to output of r
- v_i is the weight given to input i
- n is the number of units (Cooper, Seiford, et al., 2011; Medina-Borja, 2002).

The ratio that would be produced is from a single input and output. Therefore, the equation would produce a positive number result. Additional calculations would be required to resolve multiple variables and other applications such as slack, disposability, increasing/decreasing returns to scale, and many others. For this study, I decided only on the CRS and VRS concerning the organization, discussed in Chapter 3. Figure 6 is an example of a CRS frontier depiction.

Figure 6

CRS/CCR Frontier Graphical Depiction



Note. Adapted from *An Introduction to DEA* [Lecture notes on DEA]. A. Emrouznejad & E. Thanassoulis (2021). Aston Business School, Aston University, UK. In the public domain.

Figure 6 depicts five DMUs using a notional CRS frontier. The x-axis is the inputs, and the y-axis is the output variables. The CRS frontier is depicted from the origin at the x and y axis in blue. DMU 3 is efficient as it resides on the CRS frontier. On the other hand, DMU 1, 2, 4, and 5 are considered inefficient in relation to DMU 3 and do not reside on the CRS frontier. The area in the dashed green line is the production possibility set (Emrouznejad & Thanassoulis, 2020). The production possibility set is the area where all combinations of inputs and outputs for each DMU would exist. Figure 6 demonstrates that the CRS frontier is the extent of the production possibility set where DMU 3 is the most efficient than the other DMUs.

BCC/VRS model

Banker et al. developed the VRS/BCC model in 1984. Similar to CRS/CCR models, the VRS/BCC can be input or output oriented. They observed that constant returns to scale could have different results when comparing different DMUs in size (Medina-Borja, 2002). The BCC model was developed to remedy this challenge. The model does not assume proportional change as described in the CCR model. Instead, the BCC model projects the technical efficiency of different inputs and outputs regardless of the potential changes (Cooper, Seiford, et al., 2011; Majumder & Chetty, 2017).

The addition, the BCC model would constrain and envelop the data for variable returns to scale. Under the BCC model, this assumes that more DMUs are deemed efficient. This addition allows for all production to be analyzed that did not fit in the CCR assumption. In the mathematical expression, the following is provided. Figure 7 is the mathematical expression of that constrains and envelops the BCC model.

Figure 7

BCC Envelopment Equation

$$e\lambda = \sum_{j=1}^{n} \lambda_j = 1$$

Note. Reprinted from "*A non-parametric approach to evaluate the performance of social service organizations"* (p. 99), by A. Medina-Borja, 2002 ProQuest Information and Learning Company. Copyright 2006 by ProQuest Information and Learning Company. Reprinted with permission.

There are n DMUs where every DMUj, j=1, 2, . . ., n, produces the same s outputs in (possibly) different amounts, y_{rj} (r =1, 2, . . ., s), using the same m inputs, x_{ij} (i = 1, 2, . . .,m), also in (possibly) different amounts. The efficiency

> of a specific DMU*o* can be evaluated by the BCC model of DEA. (Banker et al., 2011, p. 43)

The BCC model allows for the envelopment of all the data and constrains the CCR model. The assumption is that more DMUs may be efficient, given the difference in the varying size of the DMUs to be analyzed (Medina-Borja, 2002).

Figure 8

BCC/VRS Model

$$\min\ \theta_o - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right),$$

subject to

$$\theta_o x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \qquad i = 1, 2, \ldots, m,$$

$$y_{ro} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \qquad r = 1, 2, \ldots, s,$$

$$1 = \sum_{j=1}^{n} \lambda_j,$$

$$0 \le \lambda_j, s_i^-, s_r^+ \quad \forall i, r, j,$$

Note. Reprinted from *Handbook on Data Envelopment Analysis* (p. 43) by W. W. Cooper, H. Deng, L. Seiford, and J. Zhu. (2011). Springer. (https://doi.org/10.1007/978-1-4419-6151-8_1). Copyright 2011 by Springer. Reprinted with permission.

Where

- Technical efficiency =
- $\min\ \theta_o - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$
- *j* is the DMU
- *n* is the number of units
- *i* is the number of inputs
- *r* is the number of outputs

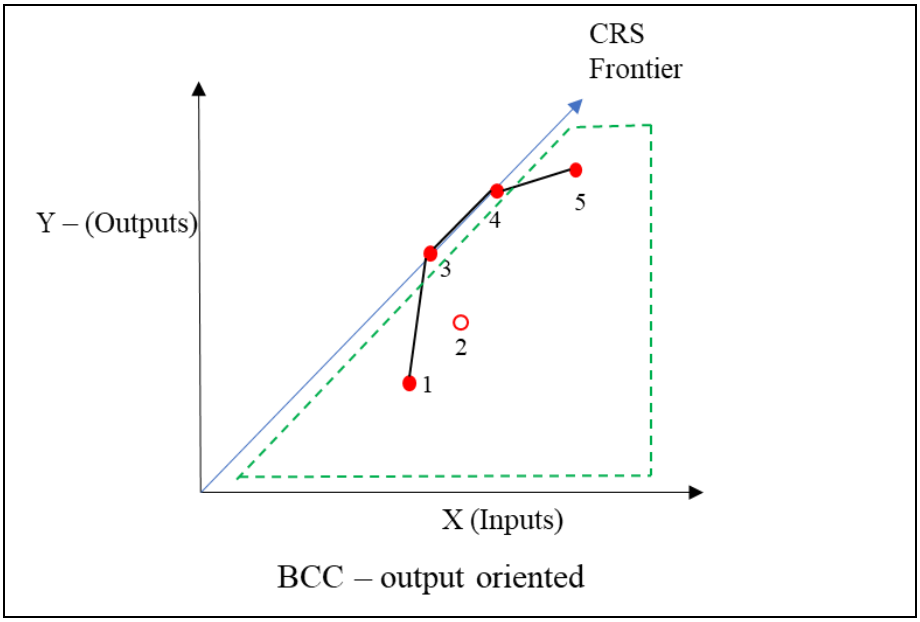
- y_{rj} is the output from r to unit j
- x_{ij} is the input of i to unit j
- u_r is the weight given to output of r
- v_i is the weight given to input i
- s_i *and* s_r is the number of outputs in different amounts that are related to i and r (Banker et al., 2011; Medina-Borja, 2002).

Figure 9 is a notional representation of a VRS graphic model to graphically portray a difference between the CRS and the VRS models. Figure 8 depicts five DMUs using a notional VRS frontier. The x-axis is the inputs, and the y-axis is the output variables. The CRS frontier is depicted from the origin at the x and y axis in blue. However, in VRS the frontier is annotated by the connection between DMUs 1, 3, 4, and 5 as the VRS frontier. The VRS frontier does not reside on the CRS frontier except for DMUs 3 and 4. In the VRS notational model, DMUs 1, 3, 4, and 5 are considered efficient. Both DMUs 3 and 4 also reside on the CRS frontier. DMU 2 is not regarded as efficient compared to the other DMUs because it does not reside on the VRS frontier.

The area in the dashed green line is the production possibility set. The production possibility set is the area where all combinations of inputs and outputs for each DMU would exist. Figure 9 demonstrates the CRS frontier is the extent of the production possibility set.

Figure 9

VRS/BCC Frontier Graphical Depiction



Note. Adapted from *An Introduction to DEA* [Lecture notes on DEA]. A. Emrouznejad & E. Thanassoulis (2021). Aston Business School, Aston University, UK. In the public domain.

External Factors

DEA has historically been assumed to be a quantitative analysis of continuous data for the input and output variables when analyzing a set of DMUs. The reality, however, is the real world does not utilize continuous information alone. For example, many organizations will rank the performance of their organizations' departments using DEA (Cook & Zhu, 2005). Rank scoring can consist of a 1-5 Likert scale or high, medium, and low scores to evaluate their organizations. For example, Likert scores are often used in surveys to assess customer satisfaction. A qualitative perspective is required for DEA to support many industries using discrete information. In many cases, mixing continuous and discrete data (e.g., personnel, operating costs [continuous], and Likert scale [discrete]) may be the norm in evaluating many DEA efforts. DEA models have been adjusted to address this concern.

This study used both continuous and discrete data. Continuous data has often been used for both inputs and outputs for DEA applications. Categorical data can also be used in DEA applications because organizations use this type of information to evaluate their operations. A discussion of categorical data, therefore, was needed for this study.

Likert scales and ordinal rankings can be characterized as discrete or categorical data and incorporated in DEA models. This was resolved by Banker and Morey (1986) by developing a separate formulation to address the environmental variable(s) that are characterized as noncontrollable characteristics. In Banker and Morey, they used the example for banks' competition in each geographical area. These could be categorized as “mild, medium, or difficult” (Banker & Morey, 1986, p. 1614). Their discussion described how one could address the discretionary inputs, e.g., management-controlled variables, followed by the nondiscretionary (uncontrolled variables), then the outputs to derive an efficiency comparison among the DMUs (Banker & Morey, 1986). The separation or handling of the differing variables is unique because it differs from the traditional DEA formulations. However, the handling of the variables is consistent with the BCC modeling in DEA (Banker et al., 1984).

Fried et al. (1999) described the all-in-one concept incorporating environmental variables as inputs and/or outputs. This assumes that categorical variables are treated similarly to the continuous inputs and outputs. The advantage of this concept is that it incorporates environmental variables, which were previously restricted. The resulting efficiency score considers the environmental variables. The confusion becomes whether the environmental variable is used as an input or output. If applied as an input, then the assumption is that it may impact the output variable. Conversely, if applied as an output, the input variable would affect the environmental output variable (Fried et al., 1999).

In their study, Cook and Zhu (2005) tested both the use and characterization for both continuous and discrete variables. There was no significant difference when using either CRS or VRS for measuring the efficiency of the DMUs. The results were equivalent for efficiency comparisons of the DMUs (Cook & Zhu, 2005). However, the results varied when using only ordinal or rankings as both input and output variables. This has been characterized as imprecise DEA or IDEA. As an IDEA, additional DEA modeling would be required for both CRS and VRS projections of efficiency (Cook & Zhu, 2005).

There are external factors that challenge humanitarian organizations in many countries. These can consist of host nation policies and practices, environmental factors, conflict, corruption, poverty, to name a few. Evaluating the organization's country operations are no different. However, the omitted exogenous factors may not highlight the operational effects or discover potential best practices within an organization when assessing efficiency (Medina-Borja, 2002).

For this study, discrete data consisting of both the conflict and corruption indexes are ordinal rankings. This study compared and evaluated the efficiency scores when these ordinal elements were introduced. The rank values for conflict and corruption indexes are exogenous to the organization. These variables are outside management's control for the organization (Cook et al., 2011).

DEA Conceptual Areas

Malmquist Productivity Index

DEA uses the Malmquist productivity index to compare and measure efficiency over time (Färe et al., 2011; Tone, 2004). The Malmquist approach would be applied to identify efficiency changes during two or more different periods. In addition, using the Malmquist productivity index would determine if improvements, e.g., efficiency, has been achieved between the benchmark and measure improvement (Färe et al., 2011; Tone, 2004). As discussed in Chapter 1, the Malmquist index was not used in this study. However, the Malmquist productivity index could be applied to the organization comparing the efficiency of their DMUs over time. Although there is incomplete data from previous years for the variables to be discussed, the Malmquist index can be used in the future to measure the efficiency of their DMUs.

Slack

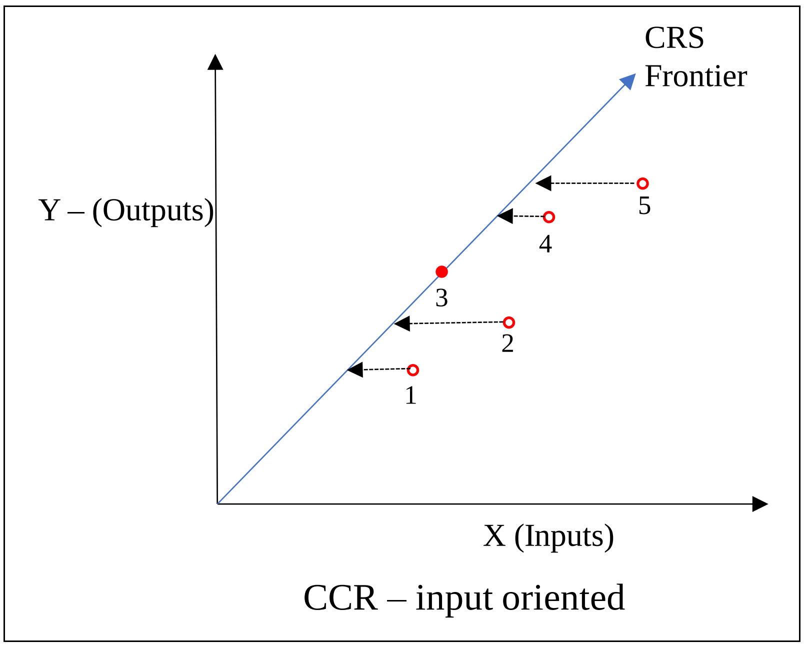
In DEA, there are two types of Slack-based models. They are radial and nonradial slack. CCR models are represented as radial where proportional changes to inputs and outputs are portrayed. For example, a proportional increase input would have a proportional change in the output. However, these changes may not reflect an accurate efficiency score if slack is ignored (Tone, 2001). For example, if the company provides a significant increase in resources, the corresponding output may not be captured if looking only at the efficiency score. A CCR model efficiency score may misrepresent a given DMU's resulting difference in input compared to the efficient DMU. Therefore, one is left with nonradial slacks contributions.

Nonradial slack sets aside the proportional assumptions in the CCR for slack-based efficiency models or SBM. Nonradial slack models are often used in VRS models where the slack has been expanded to the maximum amount to measure efficiency (Tone, 2001).

In simpler terms, a DMU may potentially reduce an input to achieve a higher efficiency corresponding to the efficient DMU. This is an indication that the inputs may be in excess when compared to the efficient DMU. In DEA literature, this would be considered as efficiently weak. Figure 10 represents the frontier projection of slack using the CCR input orientation. The x-axis represents the Inputs. The y-axis represents the outputs. The constant returns to scale (CRS) frontier is the (blue) line that begins at the origin of the x and y axis. Point 3 represents an efficient DMU because this DMU falls on the CRS frontier line. The interpretation is that the inputs and outputs are proportional to all other DMU points plotted. For example, points 1, 2, 4, and 5 reside to the right of the CRS line. This can be interpreted as excessive inputs and considered inefficient compared to point 3.

Figure 10

CCR Input Orientation

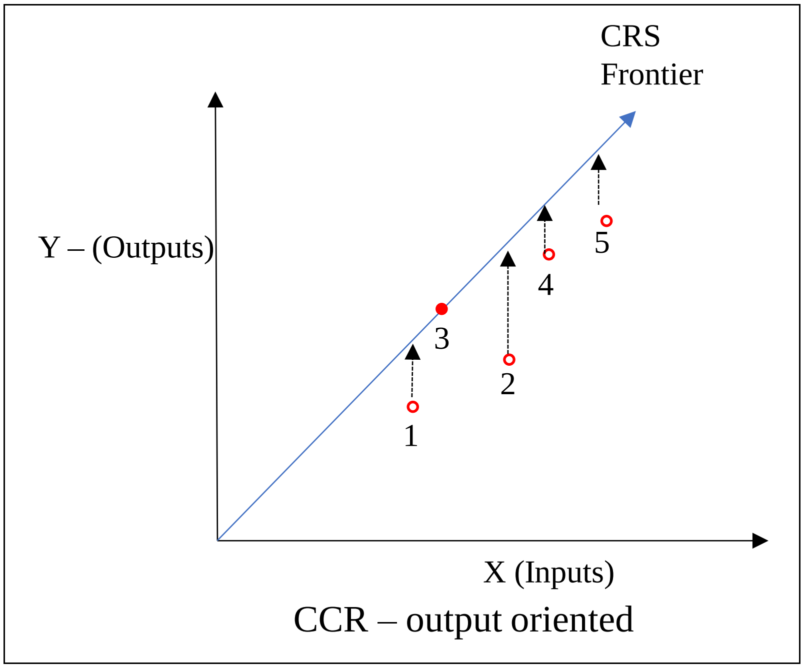


Note. Adapted from *Handbook on Data Envelopment Analysis* (p. 15) by W. W Cooper, L. M. Seiford, and J. Zhu., 2011, Springer. Copyright 2011 by Springer Science+Business Media, LLC. Reprinted with permission.

A similar example is depicted in Figure 11 using an output-oriented CCR model. As an output-oriented model, the slack or, in this case, a surplus is projected. Again, point 3 is deemed efficient. However, points 1, 2, 4, and 5 are not considered efficient, compared to point 3 as the efficient DMU. To become efficient and reside on the CRS vector, points 1, 2, 4, and 5 need to increase their respective Y outputs.

Figure 11

CCR Output Orientation



Note. Adapted from *Handbook on Data Envelopment Analysis* (p. 16) by W. W Cooper, L. M. Seiford, and J. Zhu., 2011, Springer. Copyright 2011 by Springer Science+Business Media, LLC. Reprinted with permission.

Slack becomes significant when diagnosing management decision(s) to increase or decrease inputs and how much.

Congestion

Congestion is defined when an output can be maximized by reducing one or more inputs without improving the performance of the other inputs or outputs. One can visualize this in a mining scenario. The overall objective is to increase the production (output) of the ore being mined. If the mining company increases the number of miners, one would assume the increase in the number of miners would improve the output of ore being mined. However, there is a limit to maximizing the output (Cooper, Deng, et al., 2011).

Additionally, suppose the miners are organized into teams with specific tasks. In that case, one could have improved the input, but a decreasing output of ore being mined could occur due to the team's specified duties, which may not be mining the ore. Before and after the additional miners, the difference between ore production output would demonstrate the concept of congestion due to the output losses (Cooper, Deng, et al., 2011). Many businesses assume that if a company adds additional staff, productivity may improve, and operations become more efficient. However, the concept of congestion suggests that adding other personnel may have diminishing returns and impact the output of a process.

Chance-constrained DEA Model

The chance-constrained DEA model replaces the perception of absolute characterization of DEA. In a traditional DEA approach, there are efficient and not efficient DMUs. The chance-constrained DEA re-characterizes the terminology with probably efficient to probably inefficient. This could be caused by not making the correct assumptions or inferences regarding the performance of a DMU (Cooper, Huang, et al., 2011). The potential uses for this model would be to compare peer or competing organizations or companies. For example, a competing company may make assumptions about a peer competitor without the requisite internal measures of the competitor. This would allow a company's management to develop a process that would enable the company to reduce costs and improve productivity against a peer competitor (Cooper, Huang, et al., 2011).

Weights

Weights are management judgments of corresponding inputs or outputs when attempting the optimization process or study. However, management should have some empirical evidence before assigning weights when making these judgments (Wong & Beasley, 1990). First, the initial computational runs for efficiency should be conducted without the weights. This may provide insights into where a decision can be made to assign weights to a variable. Management may believe that some variables are under- or over-rated in the initial efficiency calculations (Wong & Beasley, 1990). In this study, there are two input variables, budget and personnel. Some in management may believe that personnel are the most critical variable and can elect to weight the personnel by a given percentage. The reasoning for using weights is that a DMU efficiency score may be uncharacteristically efficient. Simply, the number of personnel may or may not support the given output in the optimization process. Conversely, a low weight may effectively nullify efficiency calculation in the resulting score (Dyson & Thanassoulis, 1988).

Weight application provides flexibility to the practitioner and management in the optimization process. Applying weights to DEA modeling can create insights into scenarios and allow management perspectives in the decision-making process. In this study, weights were not used. A management dialogue would be required, which is out of scope for this study.

Sample Size

DEA is a benchmarking application that measures a DMU's performance efficiency. In statistical analysis, a priori analysis is often required to determine a statistical model's sample size and power (Cook et al., 2014). Data envelopment analysis is not a statistical tool but a linear programming model that measures the efficiency of homogeneous units. Some DEA researchers have suggested that the number of DMUs should be "twice the number of inputs and outputs" (Zhu, 2014, p. 7; see also Golany & Roll, 1989). Other DEA experts have argued that the number of DMUs is three times the number of inputs and outputs combined (Banker et al., 1989; Bowlin, 1998). However, this is not a requirement for DEA. The number of DMUs compared to the inputs and outputs has not been proven statistically (Zhu, 2014). One could consider the above as rules of thumb or guidelines for DEA.

Balanced Scorecards

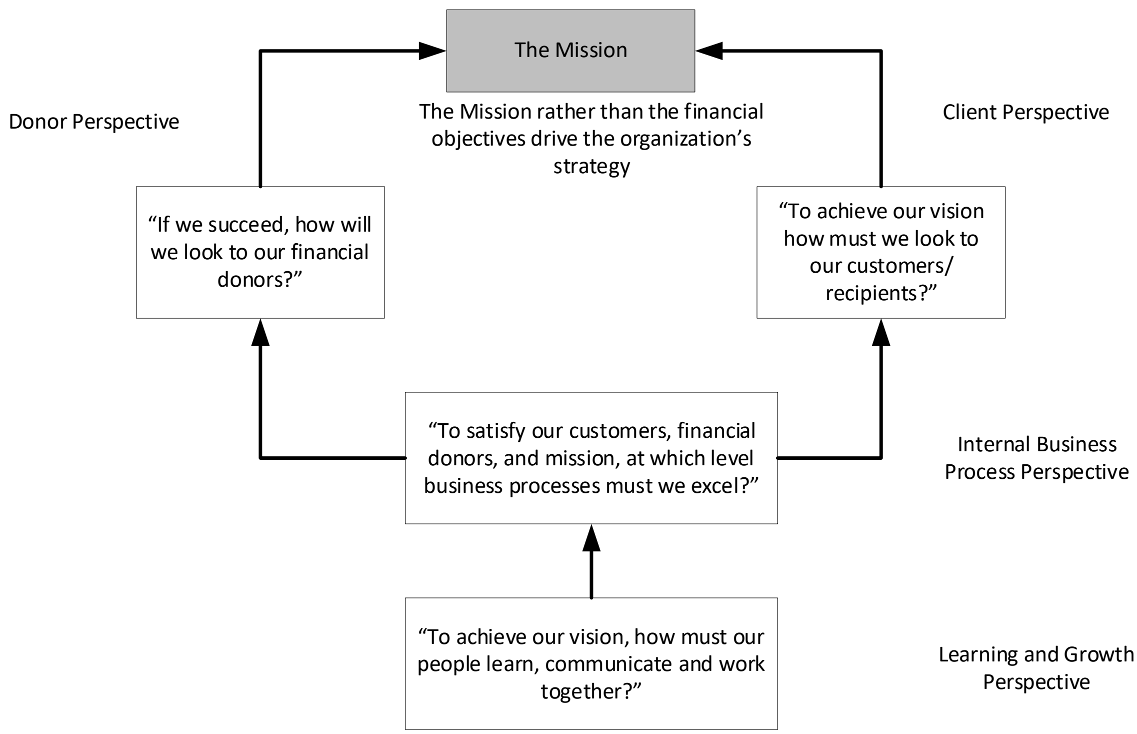
Balanced scorecards were developed by two Harvard researchers (Kaplan & Norton, 1992). Kaplan and Norton identified some disadvantages of primarily using financial reports as a performance management tool (Soysa et al., 2019). The balanced scorecards initially capture additional areas that included innovation and learning, business processes, customer, and financial measures (Soysa et al., 2019). The balanced scorecards were created to capture and report other performance indicators to understand organizational performance better and meet an organization's strategy. The dilemma for benchmarks or scorecards is the multiple measures that are collected and reported. It is uncommon for a single reported measure to satisfy a performance evaluation. For example, return on investment (ROI) may suffice from a financial perspective; however, it may not consider the operational efficiency within the organization (Zhu, 2014).

In the nonprofit sector, the financial indicator may not be the primary source of performance. Nonprofits often rely on government grants or donations as their sole element of revenue generation. However, fundraising efforts are also important for nonprofit organizations to capture and report. Performance metrics and the number of beneficiaries served are essential indicators for donors and communities where nonprofits operate. This illustrates that there are complex indicators to capture and measure for INGOs.

Kaplan (2001) created a nonprofit version where "mission drives the strategy" (Soysa et al., 2019, p. 1008), which is not solely based on financial reporting and incorporates the recipients of the services provided. Figure 12 depicts Kaplan's nonprofit framework for balanced scorecards. Essentially, Kaplan (2001) asks three questions modifying the balanced scorecard approach for nonprofits. These modifications are to address performance, external growth (fundraising), expenses and income, community building, customer satisfaction, and the effectiveness of the services provided for nonprofit organizations.

Figure 12

Nonprofit Balanced Scorecard Framework



Note. Adapted from "The Strategic Performance Measurement and Management in Nonprofit Organizations," by R. S Kaplan (2001), *Nonprofit Management & Leadership,11*(3), p. 361 (https:// doi:10.1002/nml.11308). Copyright 2001 by John Wiley & Sons, Inc. Adapted with permission.

Zimmerman (2009) expanded on the balanced scorecard approach for nonprofits and identified six reporting areas. These consist of (a) revenue and funding, (b) resource allocation (budgets), (c) products and service recipients, (d) donors and board members, (e) internal operations, and (f) staff development (Zimmerman, 2009).

Many nonprofit organizations use various performance measures to monitor their organizational needs. These organizations may refer to the practical or efficient use of the resources that have been provided to them. However, as one could argue, performance is being measured, but is the efficiency of those resources truly being captured using the balanced scorecard approach? Ultimately, the balanced scorecard addresses whether an organization effectively and efficiently meets its mission. Periodic reporting (e.g., quarterly performance reports) may be the norm for many commercial and nonprofit organizations. Under Zimmerman's approach, a DEA metric could reside in the internal operations and incorporate the other categories above in an overall balanced scorecard approach. A deliberate and conscious addition of an efficiency metric to the nonprofit balanced scorecard may add value to this approach.

I am not advocating to dismiss the balanced scorecard. On the contrary, the balanced scorecard is a proven management application for many INGO and commercial sectors. However, Sherman and Zhu (2013) have advocated integrating DEA into the balanced scorecard approach. Integrating DEA applications and their results to measure the efficiency of the resources reported in the balanced scorecard would be an additional perspective for any INGO or commercial business organization. This would be a change or an addition to the norm of balanced scorecards that incorporate DEA methodologies and their results.

DEA Software

As an operational research application, DEA has undergone many adaptions and developments since its original construct by Charnes et al. (1978). Previous DEA applications resided in the realm of academia and operational researchers. However, DEA applications have migrated from the academic research area to the practitioner over the years.

Many DEA applications are available to both practitioners and academia today. Incorporating DEA software applications as a benchmarking or decision-making tool is no longer challenging. The interoperability and integration of modeling options, large data sets, and other capabilities have made DEA analysis a relatively inexpensive proposition for companies and researchers to use (Barr, 2004). These applications continue to be adapted and improved over the years.

Today several DEA software applications provide a graphic user interface or GUI. The GUI interface has simplified many aspects of DEA computational requirements without macros, computer coding language, and other technical requirements for the user. The preponderance of these applications has been developed and designed for PC (personal computing) platforms. Apple operating systems can be used, provided the hard drive is partitioned for PC applications.

I previewed several DEA applications to support this study. Barr's (2004) criteria outline is still a viable framework for DEA users to reference software selection. The evaluation criteria considered six areas:

- Available DEA model – Most software packages have CCR/CRS and BCC/VRS packages. However, other software may not have other applications, such as Malmquist indexing, Bootstrapping, Slack, Cross Efficiency, and other capabilities.
- DEA Features and capabilities – These DEA features would include input/output/nonoriented orientations, super efficiency scores, disposability, the ability to create multiple models to compare DEA scenarios.
- Platform Interoperability – Identifying various platform operability (e.g., PC, Apple, Linux). Additionally, the interoperability uses other software tools to generate and import data into a DEA application tool, e.g., Excel, SPSS, SAS, STATA, and other applications.

- User Interface – This can range from command inputs to a graphic user interface (GUI). The ability to edit datasets or define the DMUs, inputs, outputs, and selection of DEA modeling or other desired processes. Other features included the ease of report generation in different formats and re-purposing.
- Reporting – Standardized formats can be utilized and customized for re-purposing depending on a user's requirements. Reports may consist of graphics, data tables, and other helpful information.
- Documentation and Support – Tutorials, manuals, and other guides to support users' needs and other requirements. Help menus, technical support, or websites that would assist a user if an issue were to occur with the software application or questions on DEA processes.

Several software applications were reviewed in an ad hoc manner using the above criteria. The GUI applications that were reviewed were Frontier Analyst and PIM-DEA software. Command-driven applications included Microsoft Excel using the Solver tool and R statistical software.

One of the first was Microsoft Excel, with the solver tool as a linear program optimizer. Data entry and programing could be complicated for a novice Excel user. Computer language and macros commands were required to utilize Excel as a DEA application. Excel using the solver tool could provide simplified reports and graphics for DEA interpretation. However, a limitation of Excel was the number of DMUs that could be calculated in the software application itself (Barr, 2004).

Additionally, there is no support site dedicated to resolving systems or programming issues should that occur. Instead, one should reference *Quantitative Models for Performance*

Evaluation and Benchmarking by Zhu (2014). This publication is comprehensive for using Microsoft Excel as a DEA application.

R statistical software can conduct CCR and BCC modeling, slack, and other DEA analytics. For R statistical software, the user must upload the benchmark package for DEA use. Using the benchmark package, the default in R was for CCR/CRS models. Therefore, a user would need to replace the CCR coding for BCC modeling applications (Bogetoft & Otto, 2020; Research Hub, 2020). Report and table generation were produced when appropriate coding was applied to the R software.

The Frontier Analyst can perform CRS and VRS with input/output orientation. As a result, the graphics, efficiency scores, slack, report generation, and DMU comparisons were readily available when applied. In addition, reports and graphics could quickly be produced and exported for use (Husain & Jones, 2010).

The PIM-DEA software appeared to be a complete application for DEA use. When models were developed, results, efficiency comparisons, graphics, statistical tables, reports, and other areas were readily available. Several different applications could be implemented using point and click selection of models. A user could create many different modeling scenarios with relative ease for comparison (Emrouznejad & Thanassoulis, n.d.)

I gravitated toward the GUI software applications due to their ease of use. Ultimately, PIM-DEA software was chosen due to the GUI interface, input/output orientation, modeling capabilities, graphical and textual outputs or results, ease of importing and exporting data, and costs. Chapter 3 discusses the specific methodology for this study utilizing this software. There are other DEA applications on the market. However, due to time constraints and costs, these were not investigated. The selection of DEA software for the user will ultimately come down to personal preference (e.g., cost, usability, and comfort), as with any computer or software application.

Research Variables

The following is a description of the variables used in this study. In DEA, there are essentially input and output variables used to derive the efficiency level of a DMU. I applied the budget and personnel for this study as the input variables. In the PIM-DEA software, these are also referred to as management-controlled variables. The output variable was the number of beneficiaries who were served. According to each grant agreement, the beneficiaries served are key performance indicators and periodically reported to the donors. Lastly, there were two uncontrolled variables introduced in this study. They are the corruption and conflict variables. Each of the organization's country programs operates in an environment where varying levels of conflict and corruption are present.

Budget (Input Variable - Discretionary)

The budget variable is the direct costs for each country's programming portfolio. The budget is the total operational costs for each country's portfolio. This includes procurement, operations and maintenance, and staff costs. The budget variable is a proxy for all programmatic, operational costs. There is research that supports the aggregation of these costs. Färe and Grosskopf (1985) demonstrated that technical efficiency could be achieved when all inputs were aggregated in total costs. From an economics perspective, variables' aggregation has been relied on to support economic theory and results (Zelenyuk, 2020). In terms of DEA handling big data, an aggregation of variables acts as a proxy is being researched in the application of DEA modeling (Zelenyuk, 2020). Lastly, through consultation with Thanassoulis and Emrouzenjad (July 15, 2021), the budget variable was recommended to capture all the aggregate costs. The budget variable is a discretionary variable, and the country program management team can choose how those resources may be used. Second, it simplifies the modeling efforts to consolidate these costs (Emrouznejad & Thanassoulis, 2021).

The NICRA or indirect costs are omitted. First, the NICRA varies among each donor's grant agreement. Depending on the donor, these indirect cost percentages can vary between 7% to as high as 25%. Second, NICRA costs are not a measure of efficiency related to the inputs and outputs of program implementation (Coupet & Berrett, 2018). Third, the indirect costs may not be associated with direct program implementation costs, which can skew the budgets in the aggregate. The finance department reported this variable from the organization.

Personnel (Input Variable - Discretionary)

Personnel consists of the number of employees, consultants, and volunteers who provided administrative support and program implementation at the country level. This variable is an average of the number of employees over the calendar year 2020 period. Throughout this research, grant programs were opened, closed, or extended throughout the period covered. In addition, the number of employees could change monthly due to the status of a grant or through other attrition. Therefore, the number of personnel was derived as the average number of employees, consultants, and volunteers over calendar 2020. This variable was reported from the human resources department of the organization.

Beneficiaries (Output Variable)

This variable is the total number of beneficiaries who received support or services from the organization from a particular country team. This variable is an output variable and is often reported periodically to the various grant donors, determined by each grant agreement. In addition, this metric was reported by the organization's monitoring, evaluation, accountability, and learning (MEAL) department.

Corruption (Input Variable – Nondiscretionary)

Transparency International produces a corruption perception index (CPI) each calendar year. The CPI aggregates data from many different sources that provide business and country experts on the perceived level of corruption. For calendar 2020, the CPI applied up to thirteen various data sources[2]. The CPI ranks countries from 0-100. A ranking of zero is the highest level of corruption. A 100 is perceived as the lowest level of corruption. For 2020, the CPI rankings were from 88 (low corruption) to 12 (high corruption).

In many countries where the organization operates, the CPI indicates a level of corruption in the public sector. The CPI assessment captures, at some level, the indicators of “bribery, diversion of public funding, use of public office for private gain, nepotism, and state capture” (Transparency International, 2021, para. 8). The derivative effects for INGOs that operate in low-scoring countries are the potential for additional internal process mechanisms that protect an organization from these corruption characteristics. These additional mechanisms would be an added cost and internal controls leveraged on a country program team to conduct and implement humanitarian aid operations.

Conflict (Input Variable – Nondiscretionary)

The University of Gothenburg (2021) produces the conflict index. The conflict indexes were sourced from the Quality of Government Standard Dataset and are current for 2020. The

[2] Description of the data sources used for CPI index for calendar year 2020 can be found at https://images.transparencycdn.org/images/CPI_20_SourceDescription_EN.pdf

conflict index is on a scale from 1 to 10. Thus, one represents no conflict, and ten portrays a country in conflict or conventional warfare in 2020 (Teorell et al., 2021).

Conflict has a negative impact on the ability of humanitarian aid organizations to perform relief efforts when there is conflict. This has been demonstrated over the last ten years in Syria, for instance, during its civil war (2011–present). Humanitarian access to areas of conflict has been curtailed during this time. Humanitarian aid organizations have become creative in providing aid in Syria. Remote management of operations in neighboring countries and a reliance on local organizations while the war continues. This has hampered logistics, safety, and aid efforts in the region. During this civil war, relief efforts have been impacted (Duclos et al., 2019; Leenders & Mansour, 2018).

More recently, in the Tigray region of Ethiopia, the warring factions have restricted humanitarian aid organizations' access to the conflict zone. As a result, a humanitarian aid organization's ability to deliver relief efforts has been restricted due to the lack of access, preventing aid relief, and distributing food, medical, and other supplies (Gerth-Niculescu, 2021).

The Conflict variable was necessary to evaluate the DEA analysis with this nondiscretionary variable to affect the efficiency scores of the countries in this study.

Summary

As discussed in this chapter, DEA is a versatile tool for INGOs to identify efficient operations and identify areas of improvement within their respective operations. I discussed key reasons why DEA should be used. Currently, DEA is not widely used by either donors or INGOs. Donors expect INGOs to be good stewards of their resources to implement a humanitarian aid project. Donors monitor the programs that they support through reporting and audits. DEA provides both donors and INGOs with an application to determine the efficiency of the humanitarian aid projects, either through a proposal or postimplementation process.

I discussed the primary philosophical and pragmatic approach to evaluating results and performance through audits and self-reporting to the donors. This has been the standard for over four decades. The performance evaluation has been driven by the donor and grant agreements. I advocated an addition to the evaluation criteria based on the efficiency models presented in DEA. DEA would be a paradigm shift for donors and INGOs. It is unlikely that INGOs will take the lead to transition and adopt DEA as a tool. History has shown that the donors have driven changes in the humanitarian space, which directs the INGOs to adopt a donor’s requirements and rule sets. It would be advantageous for INGOs to evaluate their own efficiency concerning the programs they are responsible for implementing. The enhancement of an INGO’s efficiency would present the capability to enhance their results, performance, and efficiency, overall, meeting the donors' needs and the communities they serve.

In Chapter 3, I discuss the mixed method design. First, the quantitative aspect of this design used the applicable variables, PIM DEA software, and DEA utilizing the CRS and VRS models. The outcome was to derive efficiency scores, slack, and target areas for improvement in this study. Second, the qualitative element addressed the design, the conduct, and procedures for collection and analysis for the focus group.

Chapter 3. Methodology and Procedures

This chapter describes the research methods, design, data collection, and other procedures for this quantitative study using DEA.

This research aimed to benchmark and measure the efficiency of an International NGO. This study used an explanatory sequential mixed methods design (Creswell & Creswell, 2018), including a quantitative method that utilized a DEA approach to measure the organization's efficiency for each county portfolio. In addition, this study used a focus group as the qualitative method. The focus group aim was to identify potential issues that can arise from using DEA to evaluate humanitarian aid programs and NGOs. This perspective was obtained from researchers who performed DEA evaluations on humanitarian programs (Alda & Cuesta, 2019; Martin-Perez & Martin-Cruz, 2017). Previous research used DEA to determine the efficiency of humanitarian aid programs; however, there is a gap from a qualitative perspective regarding the impact of these and other studies.

In this study, the primary variables were direct costs (budget) of the country portfolio, staff, and the beneficiaries served during the observation period. The standard scale in DEA determines how DMUs are efficient among homogenous units. The scale of efficiency is 1.00, meaning that the DMU is efficient. Less than 1.00 (< 1.00) determines that the DMU is inefficient compared to the efficient DMU.

The efficiencies were assessed to reflect the scope of resource conservation. An input orientation focuses on conserving resources without impacting the outputs. The input orientation measures the proportion of observed input levels that can be reduced for a given output level. Conversely, an output orientation is focused on the output variable(s) without additional resources. An output orientation model observes the maximum output levels for the given input levels (Emrouznejad & Thanassoulis, 2021).

DEA is a method for comparing homogenous operating units (e.g., hospitals to hospitals, bank branches to bank branches). DEA would be inappropriate to compare hospitals to bank branches. Additionally, not all hospitals can be compared as equals (i.e., nonprofit and for-profit hospitals). The research was a study of the efficiency of country portfolios from an International NGO.

The countries studied in this research are the following depicted in Table 4. Each country is affiliated with an operational region, the Middle East, East Africa, West Africa, and Asia. The baseline budget, staff, and beneficiaries' data were not adjusted in aggregate or disaggregated by geographical region. This was for data consistency in this study. However, the PIMDEA software could normalize the data for both the CRS and VRS models. This is discussed later in this chapter.

Table 4

Country List for Study

Geographic region	Country	Geographic region	Country	Geographic region	Country
Middle East	Iraq	East Africa/Asia	Afghanistan	West Africa	Cameroon
	Jordan		Libya		Central African Republic
	Lebanon		Ethiopia		Dem. Republic of Congo
	Syria		Pakistan		Mali
	Yemen		South Sudan		Nigeria
			Sudan		Zimbabwe
			Somalia		
			Ukraine		

DEA measures the management efficiency for a given DMU. This research compared each country's portfolio to other country portfolios. In this study, one can assume homogeneity of the DMUs. One can assume the DMUs are homogenous because the same processes and procedures, focus areas, management structure, and others are similar to the other DMUs. In Table 4, each country resides within a geographic region. This is the management structure based on the organization's policies. This is a distinction between management and policy in practice (Emrouznejad & Thanassoulis, 2021).

Additionally, this study identified areas of improvement for countries determined to be inefficient or below the 1.00 threshold. The areas of improvement are based on the variables of budget, staff, and beneficiaries.

Research Questions

There has been minimal research on the use of DEA for INGOs and the efficient use of the resources. Medina-Borja (2002), Martin-Perez and Martin-Cruz (2017), Alda and Cuesta (2019) were discussed in Chapter 2. This study demonstrated that DEA can be applied to determine the efficiency of country portfolios. The research questions were to add to the academic and operational context of using DEA as a benchmarking application.

RQ1 was to compare the efficiencies of the portfolios of the country teams using both the CRS and VRS models in the aggregate. This established a baseline for comparing the efficiency of each country in the aggregate for the organization. Therefore, RQ1 remained a valid research question for this study.

- RQ1. How do the DEA efficiency measures compare and evaluate the organization's country teams in the aggregate and within the organization's regional structure?

RQ2 was to identify the efficient DMU and compare the closest nonefficient DMUs in this study. In the operational construct, DEA peer identification can identify best practices and other processes that may assist the nonefficient DMUs to model in the future. Therefore, RQ2 was valid research for this study.

- RQ2. How do the DEA results of near peer efficiency compare to the organization's efficient vs. inefficient country teams?

RQ3 addressed areas of improvement. In DEA, this is known as slack. The slack identified a percentage where a nonefficient DMU may need to increase or decrease the input or outputs for a given variable. Therefore, RQ3 remained valid.

- RQ3. What areas and level does DEA identify areas for improvement (slack and target values) within the organization's country teams?

RQ4 was to understand if exogenous variables impact a DMU's internal processes and management. It was unknown if the exogenous variables of conflict and corruption change the outcome of an efficiency score for a given DMU. Therefore, RQ4 remained a valid question for this study.

- RQ4. Do the external variables of corruption and conflict change the efficiency of the organization's country teams?

RQ5 was to understand the potential limitations that can impact a study when DEA analyzes humanitarian aid programs. Therefore, RQ5 remained a valid question for this study.

- RQ5. What are the potential limitations of performing DEA analysis on humanitarian aid programs and organizations?

Methodological Approach

This study used an explanatory sequential mixed methods design (Creswell & Creswell, 2018). This study utilized DEA as the quantitative element and a focus group for a qualitative design element. The DEA study preceded and informed the focus group discussion.

Data Envelopment Analysis

In this study, both DEA analysis and descriptive statistics were used. The design of this study was to determine organizational capacities for a country program. Five basic units of measurement were involved in this research, as described in Chapter 2. First, was the budget variable derived from governments and institutional and private sector donors. The budget variable is a discretionary input for DEA purposes. Second, the organizational capacity (staff) was derived from the average staff personnel from each country's portfolio. Staff is considered as a discretionary input variable. Third, the beneficiary variable was the individuals who received or benefitted from services and training. The beneficiaries were the output variable. Fourth, corruption and conflict indices were exogenous variables that management had no way of controlling. Corruption and conflict indices were considered nondiscretionary variables because management has no influence over either of these variables. The corruption and conflict variables could be applied as either an input or output variable but were dependent on the model's orientation. The study used both the corruption and conflict variables in the CRS and VRS with an output orientation. Table 5 is a summary of the variables of this study.

Table 5

Data Envelopment Analysis Variables

Variable	Input or output (Variable)	Management control
Budget	Input	Discretionary
Staff	Input	Discretionary
Beneficiary	Output	Dependent
Corruption	Output	Nondiscretionary
Conflict	Output	Nondiscretionary

Focus Group

The DEA results informed the focus group. The purpose of the focus group was to understand and identify whether there are perspectives, views, and impacts using DEA to evaluate humanitarian aid programs. A qualitative perspective was necessary to understand these issues that may not be visible solely from a DEA analysis.

The focus group participants consisted of a small group of researchers who previously performed DEA on humanitarian aid programs. Therefore, it was assumed that their discussions with institutional donors and their evaluations of these programs provided insights that have not been previously discussed or researched.

Data Sources

The quantitative data were collected from the organization’s business applications and databases. The data collected were from calendar year 2020. The independent variables consist of each country’s 2020 budget and personnel staff. The outcome variable was the number of beneficiaries who received services or training from the organization’s country operations and programs during 2020.

The categorical or ordinal variables were derived from the Quality of Government Standard Dataset and Transparency International. The conflict indexes were sourced from the

Quality of Government Standard Dataset (Teorell et al., 2021). The conflict index was on a scale from 1 to 10. Therefore, one represents no conflict, and ten represent a country in conflict during 2020. The corruption index was derived from Transparency International or CPI index. The CPI index scores ranged from 88 (corruption-free) to 12 (nationwide corruption). To put the transparency index into context, Denmark was given a score of 88, meaning that the country is virtually corruption-free.

Conversely, a score of 12 was given to both South Sudan and Somalia, which indicates a high corruption rate. Both South Sudan and Somalia are countries in this study. Each country or DMU was evaluated to their respective scores based on the indexes provided from each data set.

The qualitative data collected were from the focus group discussion. The focus group consisted of researchers and practitioners who have conducted DEA analysis on humanitarian aid programs. The questions gauged their views, perspectives, issues, and impact of performing DEA.

Sample

Data Envelopment Analysis

This is a nonprobabilistic sampling of data for this DEA study. A nonprobabilistic sample can be used based on the specific research purpose of this study (Salkind, 2012). The sample consists of all international operations of the organization. The data extracted were from the organization's finance, human resources, monitoring, evaluation, accountability, learning (MEAL) departments for global operations. There is no requirement for an a priori analysis for sample size that would be required in other qualitative or quantitative studies. The data do not include headquarters information, NICRA, or emergency funded projects.

The efficiency score can rely on the number of variables in relation to the sampled DMUs. The greater the number of DMUs compared to the number of variables provides the discriminatory power to generate and evaluate the efficiency score of each DMU. Conversely, the lower the number of DMUs in relationship to the variables, the lower the discriminatory power among the DMUs (Charles et al., 2019).

As a rule of thumb, it was suggested that the number of DMUs should be at least twice the number of both inputs and outputs combined (Cook et al., 2014; Golany & Roll, 1989). Banker et al. (1989) and Bowlin (1998) suggested that DMUs should be three times the combined number of inputs and outputs. However, there is no statistical or other empirical evidence to support the above. It has been observed that many inputs and outputs and a minimal number of DMUs may lessen the discriminatory power of DEA. The rule of thumb described above was applied as standard practice in DEA techniques (Cook et al., 2014).

This study utilized twice the number of DMUs to the number of variables. There are 19 DMUs compared to three variables in phase 1 and phase 2 of this design. In phase 3, there are five variables and 19 DMUs to be evaluated. These modeling scenarios meet, at a minimum, twice the number rule of thumb for discrimination between the DMUs to be assessed.

Cook et al. (2014) compared DEA to statistical regression. Regression and sample size can be critical factors in estimating the outcomes in a set of DMUs. However, DEA is used as a benchmarking application based on the individual performance of an individual DMU. Therefore, prior specifications are not required in using basic DEA models for input and output estimates to determine efficiency (Asmild et al., 2007). In this case, “The sample size or the number of DMUs under evaluation is immaterial” (Cook et al., 2014, p. 2).

Focus Group

I solicited other researchers who have performed DEA on humanitarian aid programs to participate in this focus group. This is a small group of researchers consisting of three to five researchers. Participation in a focus group was voluntary. The questions were open-ended to guide the discussion with the focus group participants. These questions were developed for the focus group:

- Question 1: What were the donor's reactions or views from your DEA analysis?
- Question 2: What was the impact of your analysis?
- Question 3: Did you perceive any obstacles during your research effort?
- Question 4: What did you learn?
- Question 5: What would you do differently if you had to perform DEA on humanitarian aid programs or NGOs in the future?

Data Collection

Data Envelopment Analysis

The data was obtained with permission from the organization's data managers and business systems. As previously discussed, the information consisted of the country's budget, staffing, and the number of beneficiaries served. In addition, the data was requested as a part of an academic study. Finally, the information was requested in an Excel spreadsheet that allows sorting and analysis in a table construct.

The corruption, poverty, and conflict indices were collected through the Internet and downloaded from Transparency International and the Quality of Government Institute from the University of Gothenburg in Sweden. The information was rendered in an Excel spreadsheet format for sorting purposes.

Data inconsistencies or errors in the data collected were carefully reviewed (Patton, 2002). I attempted to identify these inconsistencies and resolve these data errors before DEA modeling. Because DEA is unique and an external approach to analyzing an organization's data, it can be subject to bias or other errors (Grosskopf et al., 2004). An example would be extremes in either inputs or outputs when a DMU is efficient. More importantly, if there are data errors, the shape of the data frontier may be skewed incorrectly. As a result, a DMU's relative efficiency could be underestimated (Thanassoulis, 2001).

Focus Group Discussion

I scheduled a zoom meeting with the prospective participants. The zoom meeting was recorded. The audio recording was converted to a transcript to ensure accuracy and understanding of the context of the focus group discussions. TEMI was used as the transcript tool to capture and develop the transcript for analysis.

Data Instruments

PIM DEA software (version 3.2) was the primary instrument to determine the relative efficiency of this study. The PIM DEA Software was developed by Thanassoulis and Emrouznejad (2003). Both are professors at Aston Business School, Aston University, UK. The PIM DEA software is commercially available to any consumer. I completed a two-day PIM DEA software course (see Appendix A). The hardware is a personal computer with an Intel core I7 processor, using 64-bit operations on a Windows 10 operating system.

PIM DEA is essentially a database but has the appearance of an Excel spreadsheet. It has an excellent graphical user interface over other DEA software. The selection criteria were discussed in Chapter 2 based on Barr's (2004) evaluation framework. The PIM DEA software can perform many different DEA concepts described in Chapter 2. The variables were uploaded into PIM DEA software. The rows are the country names or DMUs for the study. Each country or DMU was labeled with a three-letter identifier based on International Organization of Standards (ISO) 3166 (International Organization of Standards, n.d.). This was to declutter graphics developed and produced from the PIM DEA software (see Appendix B).

Each separate column represented the different variables. The independent or input variables (budget and staff) were categorized as discretionary input variables. Discretionary information was a variable that the management team could control. The output variable was the Beneficiaries – the number of people served in that country for calendar year 2020.

In phase three, corruption and transparency variables were added. These variables were categorized as nondiscretionary variables. Nondiscretionary variables are those that cannot be controlled by management.

I used MAXQDA software as the qualitative instrument for the focus group discussion. I used the MAXQDA software to identify and categorize keywords and phrases from the focus group discussion. MAXQDA is a qualitative analysis application. The categories captured were based on the questions previously discussed. The primary categories were views, impacts, and perspectives that may provide insights into potential issues when using DEA on humanitarian aid programs.

Data Analysis

The data analysis was conducted using statistical and DEA analysis. The mean, standard deviation, minimum and maximum in the aggregate of all countries and geographic regions were performed for statistical review purposes. The statistical analysis was to provide a first glance review of the data.

A correlation analysis was conducted on the variables in this study to examine the strength and direction in the linear relationship between the continuous variables. The correlation analysis was performed to determine collinearity among the variables (Enders, 2021). The continuous variables were the budget, personnel, and beneficiaries in this study. The Pearson correlation was applied to the continuous variables. In the Pearson correlation, a correlation coefficient produced an absolute value ranging between -1 to +1. A positive number indicated that there was a positive correlation between the variables. Conversely, a negative number showed a negative correlation. In either case, a low number does not constitute that no relationship exists, only that there may be a weak nonlinear relationship between the variables (Makarovs, 2020; Minitab, n.d.).

Lopez et al. (2016) conducted a correlation test using DEA. They concluded that high correlation values between inputs and outputs and the mean efficiency values were relatively low. It is assumed in DEA that inputs influence or are transformed into outputs in each process. Simply, there is a relationship between the inputs and outputs that derive an efficiency score. The degree of correlation between the inputs and outputs does not significantly affect the average efficiency scores. If the correlation was high, the efficiency score was increased, and conversely, for low correlation and efficiency scores.

Standard statistical hypothesis tests on sample pairs or ANOVA are inappropriate for DEA. The issue is related to the central limit theorem, which assumes normal distribution and distribution errors. In DEA, the distribution and the errors are often not normally distributed (Lopez et al., 2016). Therefore, statistical inferences applying the central limit theorem are not valid when using more than one input and one output variable (Kneip et al., 2015). There were two inputs and one output in phases 1 and 2 of this study. In phase three, there were four inputs and one output.

Modifications in the central limit theorem and data transformation are being developed for DEA applications and techniques, such as the Malmquist index or bootstrapping methods (Simar et al., 2012; Simar & Wilson, 2019). However, the Malmquist indices and bootstrapping are out of scope for this study.

Given that there are difficulties in using DEA from a statistical perspective, no statistical testing, such as T-test, ANOVA, regression, and others, were used in this study. Additionally, the number of DMU would not be enough based on an a priori analysis. For example, a minimum of 46 DMUs would be required for the paired t-test. The sample size increases for ANOVA or Regression statistical tests. This was a linear programming model; inferential statistics was the incorrect application in this endeavor. This study was a comparative analysis of the DMU's efficiency scores and related slack indications and peer relationships of the DMUs.

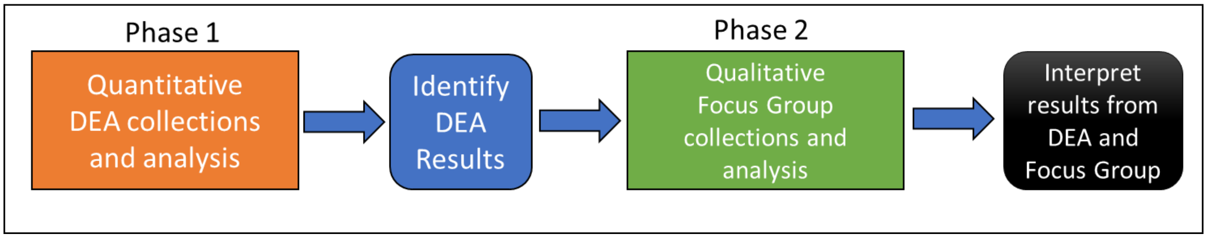
DEA was applied as previously described above. The first phase identified the efficiency of all country portfolios. An efficiency score of 1.00 demonstrated the most efficient countries. Constant returns to scale (CRS/CCR model) was used initially. The second model, variable returns to scale (VRS/BCC model), was performed to maximize the model's output. A comparison of the inefficient program to that of the closest efficient country program determined which variables should be considered for adjustment. Finally, an output orientation was used for all models. The rationale for the output orientation was driven by current donor agreements, as illustrated in the BHA indicators (USAID, 2020) and other donor agreements focused on the number of beneficiaries supported. The output orientation was a rational justification because the primary concern for INGOs is to reach the maximum number of beneficiaries (Cook et al., 2014).

Study Design

The high-level view of this explanatory sequential mixed methods design is depicted in Figure 13. First, DEA as a quantitative effort was performed to address the efficiency of the country programs. Second, the DEA results were used to inform the focus group discussion qualitatively. Lastly, the DEA analysis and focus group results were consolidated and interpreted to explain this study's results, perspectives, and context.

Figure 13

Mixed Methods - Explanatory Sequential Design



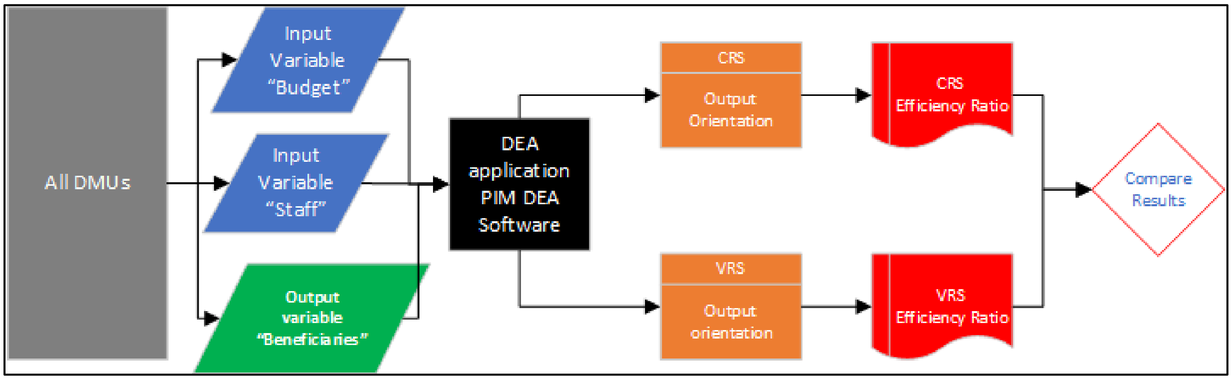
Note. Adapted from "*Research Design: Qualitative, Quantitative, Mixed Methods Approaches*," (p. 218) by J. W Creswell and J. D. Creswell, 2018. Copyright 2018 by Sage Publications, Inc. Adapted with permission.

Data Envelopment Analysis Design

The first phase compared all country teams in the aggregate to determine the efficiency, peer comparison, and slack for the studied countries. Both Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) computations were conducted using PIM DEA software. Figure 14 shows the phase 1 process flow.

Figure 14

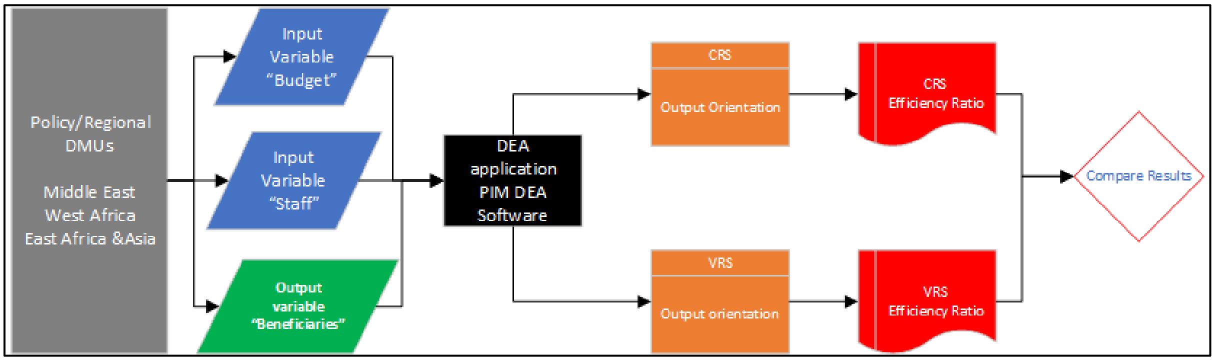
Phase 1 Design Process Flow



Second, the countries were separated into their respective geographical regions and analyzed comparing other countries within their respective areas. Because the country portfolio (DMUs) is disaggregated into their respective geographic regions, a nested design was applied to evaluate these regions' countries (Lewis-Beck et al., 2004). Both CRS and VRS efficiency scores were recalculated for each geographic region. Additionally, in phase two, peer comparisons, slack and target values were calculated. Peer comparisons were developed for this phase. The peer comparison evaluated nonefficient country programs to the closest efficient DMU peer unit. Finally, Slack numbers are based on a percentage of change and a new target value for efficiency. Figure 15 shows the phase 2 process design flow.

Figure 15

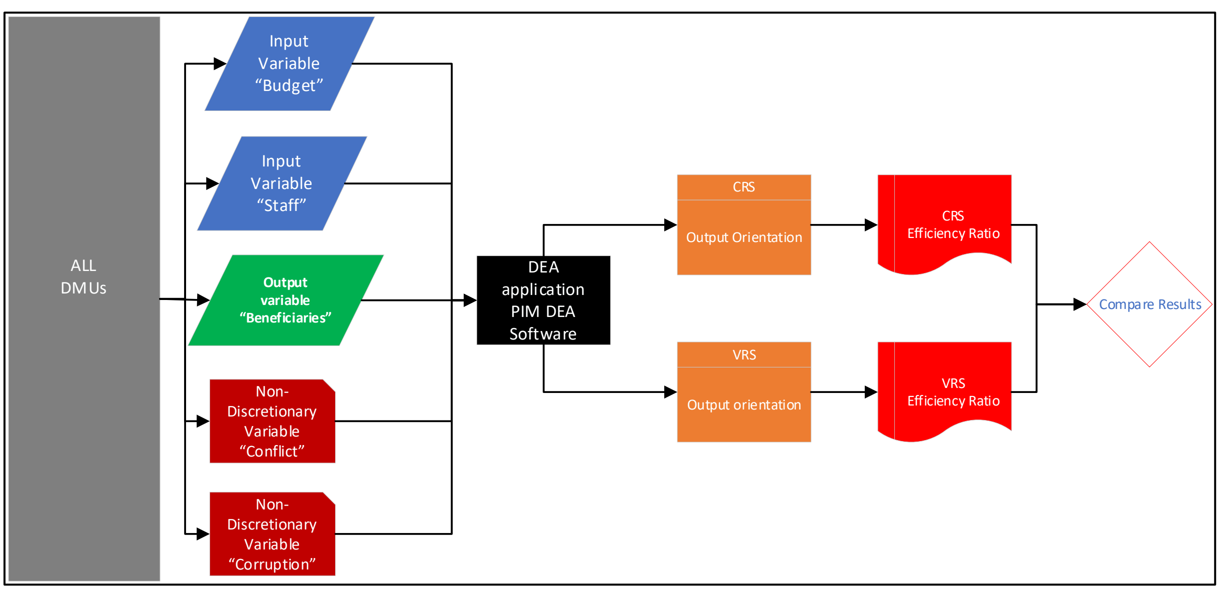
Phase 2 Design Process Flow



The third phase introduced the variables of Conflict and Corruption as nondiscretionary variables based on the environments of these countries. The purpose of measuring these nondiscretionary variables was to determine whether the variables influence the efficiency of the evaluated countries. Both CRS and VRS efficiency scores, slack, and peer comparisons were calculated. Figure 16 depicts the phase 3 design the process flow of this study

Figure 16

Phase 3 Design Process Flow



Focus Group Design

The focus group consisted of three to five researchers and practitioners of DEA who have performed studies on humanitarian aid organizations. An introduction email was sent to the prospective participants. The participants met virtually, and I coordinated a time and date for the focus group. The focus group questions, previously discussed in this chapter, guided the discussion and informed the participants in advance. This focus group was an open discussion to determine their previous work's potential limitations. The Zoom meeting application was used to conduct the virtual meeting and TEMI transcription tool.

Upon completion of the focus group, I reviewed the transcript. The transcript was coded and categorized the responses from the participants based on their views, impacts, and perspectives. Next, I identified the keywords and phrases to describe the categories and perspectives stated above. MAXQDA was the qualitative analysis application used.

Data Transformations

Linear programming at its core of DEA is an additive mathematical formula. Each variable and the corresponding lambda was calculated for each DMU. The result was the efficiency for a given DMU. A single calculation may appear in the following manner.

Variable 1 (input) = $DMU_1\lambda_1 + DMU_2\lambda_2 + DMU_3\lambda_3 + DMU_4\lambda_4 \ldots \leq DMU_1\ \theta$ (Assumes min θ) – this assumes an input orientation model. Each input and output variable was calculated similarly, using an output orientation.

Additionally, DEA equations and the PIM DEA software normalized the data, depending on the input or output orientation. Table 6 depicts an example of how this would occur. Table 6 is a notional hospital example to describe how normalizing would appear. A hospital has several doctors and nurses (input variables) who care for several outpatients (output variable) over a given time.

Table 6

Baseline and Normalized Data Example

Baseline Hospital Variables					Normalized Hospital Variables			
DMU	Doctor	Nurse	Outpatient		DMU	Doctor	Nurse	Outpatient
H01	30	72	1200		H01	25	60	1000
H02	10	50	1000		H02	10	50	1000
H03	35	20	1250		H03	28	16	1000
H04	33	44	1100		H04	30	40	1000
H05	52	91	1300		H05	40	70	1000
H06	24	40	800		H06	30	50	1000

Note: Adapted from *An Introduction to DEA* [Lecture notes on DEA]. A. Emrouznejad & E. Thanassoulis (2021). Aston Business School, Aston University, UK. In the public domain.

The PIMDEA software normalized the above variables. In this case, the outpatient variable was normalized to 1000 outpatients. The input variables were also normalized per 1000 outpatients.

I transformed a set of variables to meet an assumption in the data. Specifically, the conflict variables were transformed. As previously discussed, the ranking score for this variable was from one to ten. One is peace, and ten represents war. Because of the additive properties of linear programming, a ten may skew and misrepresent the results. First, a calculation may result in a higher efficiency score. Second, the slack and target evaluation could misrepresent the results. For example, if a DMU had a conflict index score of seven, the slack and target evaluation may recommend a target score of a ten. This would be counter-intuitive with a recommendation to increase the conflict vice de-escalating the conflict. A country at war restricts access to humanitarian aid organizations and decreases the number of beneficiaries being served. Therefore, the ranking scores were reversed. A one would then be interpreted as a country in a conflict state of war. A ten would be interpreted as a country at peace. The was a precautionary measure to address this issue in advance. This observation did occur in the DEA analysis. Chapter 4 discusses the results in the phase 3 analysis.

Human Subjects Protections

Because this is a mixed-methods study, there were two primary considerations to comply with the University of Pepperdine's Institutional Review Board (IRB) and the applicable regulations. This study was submitted and approved under exempt review by the IRB.

First, the quantitative aspect of this study used secondary data. There were no human subjects identified within these data sets. The budget consisted of financial information. The staff variable was the number of staff, volunteers, and consultants. The beneficiaries served were the number of beneficiaries who received support, services, or training from the organization. The corruption and conflict indices were ordinal ranking numbers.

The above data was requested via letter to the organization. Throughout this study, the organization was deidentified and referenced as the organization. Therefore, there is minimal risk concerning the data, the name of the organization, or persons identified within the organization.

Second, the qualitative element of this study was the focus group. The number of participants was between three and five. Only I know who the participants are for this study. The recruitment for participation in this focus group discussion was sent via e-mail to the prospective participants. Additional emails were used to coordinate and schedule the focus group. Participation in this study was strictly voluntary. The participants were self-selecting to participate in the focus group. Conversely, a participant could decline or self-select not to participate in the focus group.

The names of the participants were deidentified in the transcription tool (TEMI) and the MAXQDA qualitative analysis tool. For example, I identified as participant 1. The participants were identified as participant 2, participant 3, and participant 4. The participants' age, gender, or other demographic information are unknown and irrelevant for this study. Therefore, no personally identifiable information (PII) was requested from the participants. The focus group discussion questions were open-ended and sought to obtain the participants' potential limitations, views, perspectives, and impact when conducting their data envelopment research. There was no cognitive, aptitude, or individual testing in this study.

There was no compensation or remuneration to participate in this study. This study was a Ph.D. student study, and there was no compensation or costs related to conducting this study.

Risks

The risks were minimal. The quantitative element of this study was using secondary data with no human collection or data. The results of this study will not be released to the organization. This is an academic endeavor and not professional. There is minimal risk for a qualitative focus group. The participants in the focus group were deidentified, no PII was collected from an individual, and participation was strictly voluntary. The minimal risk that can be foreseen is the possibility of potential academic or professional discord. Examples include perspectives or views contrary to a donor organization’s culture, attitudes, or using DEA to monitor the performance of humanitarian aid programs.

Benefits

Although DEA has been used in other commercial and private sectors, DEA has rarely analyzed humanitarian aid organizations. Additionally, the views, perspectives, and potential impacts of conducting DEA have seldom been captured in academia or from a practitioner’s perspective. Thus, there is a gap in both areas. However, it is believed that this effort may begin to fill in the information in these areas.

Conclusion

This study took 60 days to conduct. Once the quantitative data were collected, reviewed, processed, and analyzed, it took 15 days to complete the DEA study. Finally, the focus group took approximately 45 days to recruit, coordinate, conduct, and explore the results. The Institutional Review Board (IRB) was approved on December 14, 2021 (see Appendix C).

Study Validity

There is a wealth of academic literature about DEA. DEA has been tested and expanded since its first conceptual framework by Charnes et al. (1978). Modifications and expansion of the DEA framework have continued over the past 40 years.

As defined by Frey (2018), the basic concept of validity refers to the "extent to which a test measures what it claims to measure" (p. 2). In this research, the instrument calculations formulated the efficiency score for each DMU compared to all other DMUs. The assumption was that each DMU and associated variables are random, homogenous, and consistent among the DMUs being measured (Frey, 2018).

Reliability is often associated with validity. Reliability refers to the extent to which the results from the instrument are free of measurement error(s). Thus, reliability and validity are complimenting concepts and are often used interchangeably. To clarify, validity refers to the instrument's accuracy, and reliability is the instrument's consistency (Frey, 2018).

There is a difference between for-profit and nonprofit organizations. For-profit organizations can evaluate net profits as a variable in DEA analysis. In contrast, nonprofits do not and may view donor requirements (e.g., the number of beneficiaries served) as a critical performance measure. A nonprofit performance and evaluation should include what good performance may resemble in a DEA evaluation. The assessment can become more complex when additional measures are added. To address this complexity, the aggregation of performance measures or metrics down to a singular performance measure is an acceptable alternative compared to for-profit organizations (Greenberg & Nunamaker, 1987).

From a subjective perspective, management in the commercial sectors and organizations has supported DEA results' validity. Many commercial and private organizations have employed various DEA techniques. An efficiency score is essentially a management evaluation tool. Therefore, a subjective response from management from a validity perspective may not be convincing or conforming to others from a broader management perspective. However, I relied on my judgment in this research and presented the information objectively (Trochim, 2002).

Summary

This study was to understand better the impact on the efficiency of the identified country programs for an INGO. DEA was applied to compare these units and to measure efficiency. An approach that has rarely been performed within the INGO community or by donors. The study design applied both CRS and VRS models with an output orientation to analyze these DMUs. Both discretionary and nondiscretionary inputs were used in a phased approach to determine the comparative efficiency among the country programs. The outcome of this design was to determine the comparative efficiencies in phases 1, 2, and 3. The efficiency scores were only one element of the efficiency assessment evaluation. Additionally, this research addressed slack, target values, and peer comparison in phases 1, 2, and 3. Twice the number of DMUs to the number of variables was applied as a rule of thumb in the phases previously described.

Additionally, this study was an opportunity to capture and better understand the potential limitations that a researcher or practitioner may encounter from a donor or organization using DEA as an application to evaluate the efficiency of humanitarian aid programs and their management. In Chapter 4, the results of this study are discussed. First, the DEA evaluation is presented as discussed in this chapter. Then, the focus group discussion results are presented following the DEA discussion.

Chapter 4. Results

This chapter addresses the results of this study, first with a focus on the study's descriptive statistics and a correlation overview. Following the statistical review, the DEA results are reviewed, as previously described in Chapter 3. Lastly are the focus group discussion results. There were no missing data elements in the variables collected.

Statistical Overview

The statistical overview is a first glance at the data variables in this study. The variables of budget (input), staff (input), beneficiaries (output), corruption, and conflict variables were reviewed. In Table 7 are the budget (M = \$14,408,858, SD = 9879479), staff (M = 376.4, SD = 281), beneficiaries (M = 695,119, SD = 590367), conflict (M =8.211, SD = 9.56), and corruption (M = 23.68, SD = 9.56). The Shapiro-Wilk normality tests were conducted on the above variables. The budget (p = 0.184), staff (p = 0.056) and corruption index (p = 0.123) meet the homogeneity of normality. The beneficiary (p = 0.022) and conflict variables (p = 0.022) did not meet the homogeneity of normality.

Iraq had the largest budget (\$32,113,081) and personnel (945) variables in these categories. Ethiopia served the most beneficiaries (20,678,873). Zimbabwe had the smallest operational budget (\$996,480) and the smallest staff (27). Finally, Ukraine had the smallest number of beneficiaries served (24,480).

The CPI Index for corruption had a mean of 23.7 (SD = 9.56). The minimum was a 12, and the maximum was a 49. The CPI index can be interpreted as the 19 countries falling in the bottom 50th percentile of all countries globally. Essentially, there are issues and challenges related to corruption in these countries.

The conflict index can be interpreted as a minimum level of unrest, to conflict within this group of countries. The conflict index had a mean of 8.37 (*SD* = 1.54). Therefore, the minimum ranking for the 19 countries was a five, with a maximum of 10. Table 7 is the descriptive statistics of the variables described above.

Table 7

Descriptive Statistics

	Budget	Staff	Beneficiaries	CPI Index	Conflict Index
N	19	19	19	19	19
Mean	1.44e+7	376	695119	23.7	8.37
Median	12369930	287	579828	24	9
Standard deviation	9.88e+6	281	590367	9.56	1.54
Minimum	996480	27	24480	12	5
Maximum	32113081	945	2067873	49	10
Shapiro-Wilk W	0.931	0.903	0.881	0.922	0.881
Shapiro-Wilk p	0.184	0.056	0.022	0.123	0.022

In Table 8, a Pearson correlation was examined to determine collinearity among the variables in this study. The correlation analysis is to understand better the relationship among each of the variables within this study. The correlation matrix helps to understand the direction (positive or negative) and the significance of the relationship among the variables. A p-value of 0.05 is the threshold for measuring the correlation's statistical significance. For example, there is a strong positive correlation between budget and staff variables ($r = 0.772$), which is statistically significant ($p < 0.001$). This makes sense because the budget will influence the number of staff hired. On the other hand, the budget and beneficiary variables were moderately correlated ($r = 0.361$) and were not statistically significant.

The staff and beneficiaries were moderately correlated ($r = 0.469$) and were statistically significant ($p < 0.05$). Again, this makes sense due to the labor-intensive work that the organization performs in these countries.

The CPI index (corruption) variable was virtually neutral among the budget ($r = 0.053$), staff ($r = 0.107$), and beneficiary ($r = -0.132$) variables. There was no significance observed among these variables. Lastly, the conflict index was virtually neutral for budget ($r = -0.033$), staff ($r = 0.082$), and beneficiaries ($r = 0.056$). There was a strong negative correlation between the CPI index and the conflict index ($r = -0.669$) that was statistically significant ($p < 0.01$). The neutral correlation between the corruption and conflict index and the budget, staff, and beneficiary variables was expected because these are outside the organization's ability to influence these areas.

Table 8

Correlation Matrix

		Budget	**Staff**	**Beneficiaries**	**CPI Index**	**Conflict Index**
Budget	Pearson's *r*	—				
	p-value	—				
Staff	Pearson's *r*	0.722 ***	—			
	p-value	< .001	—			
Beneficiaries	Pearson's *r*	0.361	0.469 *	—		
	p-value	0.129	0.043	—		
CPI Index	Pearson's *r*	0.053	0.107	-0.132	—	
	p-value	0.828	0.664	0.590	—	
Conflict Index	Pearson's *r*	-0.033	0.082	0.056	-0.669 **	—
	p-value	0.892	0.738	0.820	0.002	—

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

Phase 1 Evaluation

Phase 1 evaluation of the data envelopment analysis was the organization's 19 country operations compared in the aggregate amongst all 19 countries. The comparison was twofold. The first was to compare and identify the efficient countries among all the other countries in this analysis. The second was to determine differences between the constant returns to scale (CRS/CCR) and the variable returns to scale (VRS/BCC) models. All models have an output orientation.

Table 9 compares the efficiency of all country portfolios for both CRS and VRS models using an output orientation. The CRS models demonstrated that 10% of the DMUs were efficient. The VRS models demonstrated that 20% of the DMUs were considered efficient in the aggregate. The first number is the CRS efficiency score, and the second number is the VRS efficiency score. Cameroon (1.00/1.00) and the Democratic Republic of the Congo (1.00/1.00) were deemed efficient in both the CRS and VRS models. As noted in Chapter 2, VRS models can provide additional efficient scores. This was observed for Ethiopia (.82/1.00) and Zimbabwe (.90/1.00) being efficient under VRS modeling. In comparing the results between the CRS and VRS models, some DMUs remained the same in both models, which included Central African Republic (.45/.45), Libya (.08/.08), Nigeria (.27/.27), and Syria (.48/.48). The remaining DMUs had a modest increase in efficiency under the VRS models. The following countries had observed the modest increases between the CRS and VRS scores - countries: Afghanistan (.77/.78), Iraq (.18/.35), Jordan (.07/.13), Lebanon (.17/.19), Mali (.87/.88), Pakistan (.74/.83), Somalia (.45/.49), South Sudan (.27/.42), Sudan (.86/.98), Ukraine (.12/.15), and Yemen (.78/.79). These observations were an expected outcome comparing the CRS and VRS efficiency scores for the phase 1 model based on the literature review. The VRS efficiency scores were expected to either remain or increase when compared to the CRS model.

Table 9

Phase 1 - Efficiency Scores CRS and VRS

DMU	Description	CRS Efficiency	VRS Efficiency
AFG	Afghanistan	0.77	0.78
CMR	Cameroon	1.00	1.00
CAF	Central African Republic	0.45	0.45
COD	Dem. Republic of Congo	1.00	1.00
ETH	Ethiopia	0.82	1.00
IRQ	Iraq	0.18	0.35
JOR	Jordan	0.07	0.13
LBN	Lebanon	0.17	0.19
LBY	Libya	0.08	0.08
MLI	Mali	0.87	0.88
NGA	Nigeria	0.27	0.27
PAK	Pakistan	0.74	0.83
SOM	Somalia	0.45	0.49
SSD	South Sudan	0.27	0.42
SDN	Sudan	0.86	0.98
SYR	Syria	0.48	0.48
UKR	Ukraine	0.12	0.15
YEM	Yemen	0.78	0.79
ZWE	Zimbabwe	0.90	1.00

As discussed in Chapter 2, there would be an increase in efficient DMUs when using the VRS models compared to CRS models.

Table 10 depicts the peer comparison between the CRS and VRS models. Peer comparison illustrates the closest efficient scores compared to those inefficient DMUs. Peer comparisons establish a benchmark of the efficient DMUs that can be used as role models for the inefficient DMUs.

Cameroon (CMR) and the Democratic Republic of Congo (COD) were deemed efficient from the CRS model. Cameroon (CMR), as a peer comparison, depicts that all DMUs except the

Democratic Republic of Congo (COD) can be peers or role models for potential improvements. Seventeen other DMUs could use CMR as a role model portfolio. Conversely, COD is a role model for 12 other DMUs.

Table 10 also depicts the VRS model peer comparison. In the VRS model, four countries were deemed efficient—Cameroon (CMR), the Democratic Republic of Congo (COD), Ethiopia (ETH), and Zimbabwe (ZWE). The VRS comparison displays the peer comparison for the efficient DMUs and their frequencies - CMR (12), COD (10), ETH (6), and ZWE (9). Again, one can observe some overlap, where efficient DMUs can be a role model for the similar inefficient peers under each model. This provides flexibility to the management teams to investigate best practices that may be transferred to other peer countries to improve efficiency.

Table 10

Phase 1 - Peer Comparisons in the Aggregate

		CRS Peers		VRS Peers			
DMU	Description	CMR	COD	CMR	COD	ETH	ZWE
AFG	Afghanistan	✓		✓			✓
CMR	Cameroon	✓		✓			
CAF	Central African Republic	✓	✓	✓	✓		✓
COD	Dem. Republic of Congo		✓		✓		
ETH	Ethiopia	✓				✓	
IRQ	Iraq	✓	✓			✓	
JOR	Jordan	✓	✓		✓	✓	
LBN	Lebanon	✓	✓		✓	✓	
LBY	Libya	✓	✓	✓	✓		✓
MLI	Mali	✓	✓	✓	✓		✓
NGA	Nigeria	✓	✓	✓	✓		✓
PAK	Pakistan	✓		✓			✓
SOM	Somalia	✓		✓		✓	
SSD	South Sudan	✓	✓		✓	✓	
SDN	Sudan	✓	✓	✓	✓	✓	
SYR	Syria	✓	✓	✓	✓		✓

		CRS Peers		VRS Peers			
DMU	Description	CMR	COD	CMR	COD	ETH	ZWE
UKR	Ukraine	✓		✓			✓
YEM	Yemen	✓	✓	✓	✓		✓
ZWE	Zimbabwe	✓	✓				✓
	Frequency	18	13	13	11	7	10

Table 11 is a CRS comparison for slack, targets, and change percentage. Because the budget is fixed for the observation period, there is no change in either the slack or target numbers. Changes are observed in several data points for the staff and beneficiary variables with the corresponding percentage of change required to become more efficient. There is a recommended reduction in staff personnel for Afghanistan (AFG; -48%), Ethiopia (ETH; -32%), Pakistan (PAK; -47.5%), Somalia (SOM; -35.46%), and the Ukraine (UKR; -20.8%). The CRS model indicates that staff size could be reduced while the number of beneficiaries could be increased. Except for Cameroon (CMR) and the Democratic Republic of the Congo (COD), the CRS model indicated the potential range to increase the number of beneficiaries that could be served with the budget and staffing. The CRS model noted that a small increase in the number of beneficiaries was for Zimbabwe (ZWE; 11.76 %), while and the largest potential increase was for Jordan (JOR; 1199.93%) that could be potentially obtained with the given budget and staff.

Table 11

Phase 1 - CRS Model Slack, Targets, and Percentage of Change

CRS Model Slack, Targets and Percentage of Change									
Name	Total Budget (I) Value	Total Budget (I) Target	Total Budget (I) Gain(%)	Staff(I) Value	Staff(I) Target	Staff(I) Gain(%)	Beneficiaries(O) Value	Beneficiaries(O) Target	Beneficiaries(O) Gain(%)
AFG	6717193	6717193	0	430	223.61	-48	714542	922096.01	29.05
CMR	9853016	9853016	0	328	328	0	1352563	1352563	0
CAF	12023162	12023162	0	265	265	0	544041	1207613.67	121.97
COD	28390738	28390738	0	287	287	0	1742327	1742327	0
ETH	18272611	18272611	0	901	608.28	-32.49	2067873	2508354.55	21.3
IRQ	32113081	32113081	0	945	945	0	714542	4002179.62	460.1
JOR	31419201	31419201	0	740	740	0	254729	3311289.76	1199.93
LBN	24655937	24655937	0	351	351	0	319939	1846321.62	477.09
LBY	13385797	13385797	0	174	174	0	73975	948151.44	1181.72
MLI	5105596	5105596	0	100	100	0	408240	471774.99	15.56
NGA	13090349	13090349	0	220	220	0	294674	1090427.46	270.05
PAK	1946603	1946603	0	123	64.8	-47.32	197458	267218	35.33
SOM	12369930	12369930	0	638	411.79	-35.46	770660	1698069.87	120.34
SSD	24518654	24518654	0	710	710	0	827777	3017991.62	264.59
SDN	17815267	17815267	0	408	408	0	1582083	1839598.82	16.28
SYR	9547598	9547598	0	284	284	0	579828	1199850.9	106.93
UKR	1427497	1427497	0	60	47.52	-20.8	24480	195958.24	700.48
YEM	10119602	10119602	0	160	160	0	633136	809980.36	27.93
ZWE	996480	996480	0	27	27	0	104398	116580.1	11.67

Table 12 is a VRS comparison for slack, targets, and change percentage. Cameroon (CMR), the Democratic Republic of the Cong (COD), Ethiopia (ETH), and Zimbabwe (ZWE) were deemed efficient under the VRS modeling. There were no changes in the budget, personnel, or beneficiaries. The VRS recommended decreases in the budgets for Iraq (IRQ; -43.1%), Jordan (JOR; -33.4), and South Sudan (SSD; -12.64%). There is a recommended reduction in staff personnel for Afghanistan (AFG; -48.51%), Iraq (IRQ; -4.66%), Pakistan (PAK; -51.8%), Somalia (SOM; -21.74%), and the Ukraine (UKR; -30.59%). Changes are observed in several data points for the staff and beneficiary variables with the corresponding percentage of change required to become more efficient. The VRS model indicated a range that the number of beneficiaries could be increased with the budget and staffing changes. The VRS model noted that a minimal increase for Sudan (SDN; 1.69%) to the largest potential increase for Libya (LBY; 1174.21%) could potentially be obtained to increase the number of beneficiaries reached in the VRS phase 1 model.

Table 12

Phase 1 - VRS Comparison for Slack, Targets, and Percentage of Change

VRS Comparison for Slack, Targets and Percentage of Change									
Name	Total Budget (I) Value	Total Budget (I) Target	Total Budget (I) Gain(%)	Staff(I) Value	Staff(I) Target	Staff(I) Gain(%)	Beneficiaries(O) Value	Beneficiaries(O) Target	Beneficiaries(O) Gain(%)
AFG	6717193	6717193	0	430	221.43	-48.51	714542	910626.73	27.44
CMR	9853016	9853016	0	328	328	0	1352563	1352563	0
CAF	12023162	12023162	0	265	265	0	544041	1205402.1	121.56
COD	28390738	28390738	0	287	287	0	1742327	1742327	0
ETH	18272611	18272611	0	901	901	0	2067873	2067873	0
IRQ	32113081	18272611	-43.1	945	901	-4.66	714542	2067873	189.4
JOR	31419201	20925735.5	-33.4	740	740	0	254729	1982509.96	678.28
LBN	24655937	24655937	0	351	351	0	319939	1714515.64	435.89
LBY	13385797	13385797	0	174	174	0	73975	942596.46	1174.21
MLI	5105596	5105596	0	100	100	0	408240	462712.17	13.34
NGA	13090349	13090349	0	220	220	0	294674	1086595.62	268.74
PAK	1946603	1946603	0	123	59.29	-51.8	197458	238300.27	20.68
SOM	12369930	12369930	0	638	499.29	-21.74	770660	1566394.4	103.25
SSD	24518654	21420106.5	-12.64	710	710	0	827777	1966603.8	137.58
SDN	17815267	17815267	0	408	408	0	1582083	1608783.08	1.69
SYR	9547598	9547598	0	284	284	0	579828	1198153.26	106.64
UKR	1427497	1427497	0	60	41.65	-30.59	24480	165141.88	574.6
YEM	10119602	10119602	0	160	160	0	633136	803618.89	26.93
ZWE	996480	996480	0	27	27	0	104398	104398	0

Phase 2

Phase 2 is a breakdown by geographic regions. The organization's countries are organized within a regional construct. The regional construct is the Middle East, East Africa and Asia, and West Africa. Each region's countries were evaluated within their regional construct. First, the efficiency was assessed by employing the CRS and VRS models with an output orientation. Second, the peer comparisons are depicted within each geographic region. Lastly, the slack and theoretical targets were compared.

East Africa and Asia

East Africa and Asia consisted of eight countries. In Table 13, Ethiopia (1.00) and Sudan (1.00) were deemed efficient under the CRS model. The other six countries were considered inefficient with a less than one (< 1.00) efficiency score. Conversely, when the VRS model is applied, Ethiopia (ETH; 1.00), Sudan (1.00), Pakistan (1.00), and Ukraine (1.00) were deemed efficient.

Table 13

Phase 2 - East Africa and Asia Comparative Efficiency - CRS & VRS Model

East Africa and Asia Comparative Efficiency - CRS & VRS Model			
DMU	Country	CRS Efficiency	VRS Efficiency
AFG	Afghanistan	0.94	0.96
ETH	Ethiopia	1.00	1.00
LBY	Libya	0.11	0.14
PAK	Pakistan	0.89	1.00
SOM	Somalia	0.55	0.55
SSD	South Sudan	0.36	0.44
SDN	Sudan	1.00	1.00
UKR	Ukraine	0.16	1.00

When comparing the CRS to the VRS results, the VRS models appear to be more accommodating for efficiency. This difference between the CRS and VRS models was observed in the results for Ukraine (.16/1.00). In the CRS model, Ukraine was scored as 0.16, and the VRS was scored as efficient (1.00). Other efficiency scores remained relatively consistent for Afghanistan (AFG; .94/.96), Libya (LBY; .11/.14), Somalia (SOM; .55/.55), and South Sudan (SSD; .36/.44).

Table 14 was the peer comparison for East African and Asian countries. In the CRS peer comparisons, Ethiopia and Sudan are the efficient role models for the other countries. Most of the peers reside under Ethiopia, but there is overlap with Sudan—namely Ukraine and South Sudan. In the VRS model, Ethiopia, Pakistan, Sudan, and Ukraine were evaluated as efficient and became the remaining countries' role models. The peer comparison is more dispersed in the VRS model. Ethiopia remained the dominant peer to other efficient countries. The frequency numbers were adjusted to omit the peer country from counting itself as its peer. For example, six countries were identified under Ethiopia in the CRS model, which was the efficient peer to Afghanistan, Ethiopia, Pakistan, Somalia, South Sudan, and Ukraine. The frequency count omits Ethiopia as the peer because Ethiopia is the efficient peer compared to the other inefficient peers; this would be double-counting the efficient peer.

Table 14

Phase 2 - East Africa and Asia Peer Comparison - CRS & VRS Model

East Africa and Asia Peer Comparison - CRS & VRS Model							
		CRS Peers		VRS Peers			
		ETH	SDN	ETH	PAK	SDN	UKR
<u>DMU</u>	<u>Country</u>						
AFG	Afghanistan	✓		✓	✓		
ETH	Ethiopia	✓		✓			
LBY	Libya		✓			✓	✓
PAK	Pakistan	✓			✓		
SOM	Somalia	✓		✓	✓		
SSD	South Sudan	✓	✓	✓		✓	
SDN	Sudan		✓			✓	
UKR	Ukraine	✓	✓				✓
	Frequency	5	3	3	2	2	1

Table 15 shows the results of the CRS model for slack and targets. The preponderance of the countries' budgets remain unchanged, except for Libya. Based on the CRS model Libya's (LBY) budget could be reduced by 43.24%. The CRS model recommends a reduction in the staff for Afghanistan (AFG; -22.97%), Pakistan (PAK; -21.96%), and Somalia (SOM; -4.4%). All other staff recommendations remain unchanged. The beneficiaries variable depicts most changes in the CRS model for this region. Ethiopia (ETH) and Sudan (SUD) are zero because they are deemed efficient, and no increase in the number of beneficiaries was required. All other countries have the theoretical capacity to increase the number of beneficiaries within their country portfolios. The following are the countries that could increase their beneficiary output by percentage: Afghanistan (AFG; 6.39%), Libya (LBY; 812.08%), Pakistan (PAK; 11.56%), Somalia (SOM; 81.65%), South Sudan (SSD; 179.59%), and Ukraine (UKR; 520.76%). Applying the CRS model demonstrates the efficiency potential for reaching additional people in need.

Table 15

Phase 2 - East Africa & Asia CRS Slack and Targets

East Africa & Asia CRS Slack and Targets									
Name	Total Budget (I) Value	Total Budget (I) Target	Total Budget (I) Gain(%)	Staff(I) Value	Staff(I) Target	Staff(I) Gain(%)	Beneficiaries(O) Value	Beneficiaries(O) Target	Beneficiaries(O) Gain(%)
AFG	6717193	6717193	0	430	331.22	-22.97	714542	760170.62	6.39
ETH	18272611	18272611	0	901	901	0	2067873	2067873	0
LBY	13385797	7597687.4	-43.24	174	174	0	73975	674711.87	812.08
PAK	1946603	1946603	0	123	95.98	-21.96	197458	220292.97	11.56
SOM	12369930	12369930	0	638	609.95	-4.4	770660	1399878.99	81.65
SSD	24518654	24518654	0	710	710	0	827777	2314364.29	179.59
SDN	17815267	17815267	0	408	408	0	1582083	1582083	0
UKR	1427497	1427497	0	60	60	0	24480	151962.82	520.76

Table 16 shows the results of the VRS model for slack and targets. In the VRS model, Ethiopia (ETH), Pakistan (PAK), Sudan (SDN), and Ukraine (UKR) are deemed efficient, and no changes in the variables were noted. The preponderance of the countries' budgets remain unchanged, with the exceptions of Libya (LBY; -49.23%) and South Sudan (SSD; -26.2%), which could be reduced. The VRS model recommended a reduction in staff for Afghanistan (AFG; -18.53%) and Somalia (SOM; -2.87%). All other staff recommendations remain unchanged. The beneficiaries variable depicts most changes in the VRS model for this region. Afghanistan (AFG; 4.12%), Libya (LBY; 622.85%), Somalia (SOM; 80.58%), and South Sudan (SSD; 127.07%) theoretically could increase their output of beneficiaries. Applying the VRS demonstrates the potential for efficiency in reaching additional people in need.

Table 16

Phase 2 - East Africa and Asia VRS Slack and Targets

East Africa and Asia VRS Slack and Targets									
Name	Total Budget (I) Value	Total Budget (I) Target	Total Budget (I) Gain(%)	Staff(I) Value	Staff(I) Target	Staff(I) Gain(%)	Beneficiaries(O) Value	Beneficiaries(O) Target	Beneficiaries(O) Gain(%)
AFG	6717193	6717193	0	430	350.34	-18.53	714542	744008.21	4.12
ETH	18272611	18272611	0	901	901	0	2067873	2067873	0
LBY	13385797	6795904.4	-49.23	174	174	0	73975	534729.26	622.85
PAK	1946603	1946603	0	123	123	0	197458	197458	0
SOM	12369930	12369930	0	638	619.71	-2.87	770660	1391622.99	80.58
SSD	24518654	18095425	-26.2	710	710	0	827777	1879666.33	127.07
SDN	17815267	17815267	0	408	408	0	1582083	1582083	0
UKR	1427497	1427497	0	60	60	0	24480	24480	0

Middle East

The Middle East consisted of five countries. In Table 17, Yemen (YEM) was deemed efficient under the CRS model. The other four countries were considered inefficient with a less than one (< 1.00) efficiency score. Conversely, when the VRS model was applied, Iraq (IRQ; 1.00), Syria (SYR; 1.00), and Yemen (YEM; 1.00) were deemed efficient.

Table 17

Phase 2 - Middle East Efficiency CRS and VRS Model Comparison

Middle East Efficiency CRS and VRS Model Comparison		
Name	CRS Efficiency	VRS Efficiency
IRQ	0.35	1.00
JOR	0.12	0.36
LBN	0.23	0.49
SYR	0.97	1.00
YEM	1.00	1.00

Table 18 shows the peer comparison for the Middle East countries. In the CRS peer comparisons, Yemen (YEM) is considered the role model for the other countries in the region. In the VRS model, Iraq (IRQ), Syria (SYR), and Yemen (YEM) were evaluated as efficient and became the role models for the remaining countries. Either Iraq (IRQ) or Yemen (YEM) have a peer relationship with Jordan (JOD) and Lebanon (LBN). Syria (SYR) did not have a peer equivalent.

Table 18

Phase 2 - Middle East CRS & VRS Peer Comparisons

Middle East CRS & VRS Peer Comparisons				
	CRS Peers	VRS Peers		
Name	YEM	IRQ	SYR	YEM
IRQ	✓	✓		
JOR	✓	✓		✓
LBN	✓	✓		✓
SYR	✓		✓	
YEM	✓			✓

Table 19 shows the results for the CRS assessment for slack, target, and percentage change for the Middle East countries. Because Yemen (YEM) is efficient under the CRS model, no variable changes are recommended for Yemen. A budget reduction was recommended for Lebanon (LBN; -9.96%). No additional changes were observed for the other countries within this regional group. A staffing reduction was observed for Iraq (IRQ; -46.27%), Jordan (JOD; -32.87%), and Syria (SYR; -46.85%). All countries except Yemen (YEM) noted the potential increase in beneficiaries. The increases were Iraq (IRQ; 181.18%), Jordan (JOD; 671.7%), Lebanon (LBN; 334.13%), and Syria (SYR; 3.02%).

Table 19

Phase 2 - Middle East CRS Slack and Target Comparisons

Middle East CRS Slack and Target Comparisons									
Name	Total Budget (I) Value	Total Budget (I) Target	Total Budget (I) Gain(%)	Staff(I) Value	Staff(I) Target	Staff(I) Gain(%)	Beneficiaries(O) Value	Beneficiaries(O) Target	Beneficiaries(O) Gain(%)
IRQ	32113081	32113081	0	945	507.74	-46.27	714542	2009164.75	181.18
JOR	31419201	31419201	0	740	496.77	-32.87	254729	1965751.94	671.7
LBN	24655937	22199876.89	-9.96	351	351	0	319939	1388942.1	334.13
SYR	9547598	9547598	0	284	150.96	-46.85	579828	597348.39	3.02
YEM	10119602	10119602	0	160	160	0	633136	633136	0

Table 20 shows the VRS comparisons for slack, targets, and percentage comparisons. Because Iraq (IRQ), Syria (SYR), and Yemen (YEM) are considered efficient under the VRS model, no changes were observed for the budget, staff, and beneficiary variables. A reduction of the budget variable was recommended for Jordan (JOD; -16.07%) and Lebanon (LBN; -37.35%). There were no changes in the staff variable for the Middle East region in the VRS model. Potential increases were noted for Jordan (JOD; 172.16) and Lebanon (LBN; 104.08%).

Table 20

Phase 2 - Middle East VRS Slack and Target Comparisons

Middle East VRS Slack and Target Comparisons									
Name	Total Budget (I) Value	Total Budget (I) Target	Total Budget (I) Gain(%)	Staff(I) Value	Staff(I) Target	Staff(I) Gain(%)	Beneficiaries(O) Value	Beneficiaries(O) Target	Beneficiaries(O) Gain(%)
IRQ	32113081	32113081	0	945	945	0	714542	714542	0
JOR	31419201	26369561	-16.07	740	740	0	254729	693283.11	172.16
LBN	24655937	15470882	-37.25	351	351	0	319939	652943.06	104.08
SYR	9547598	9547598	0	284	284	0	579828	579828	0
YEM	10119602	10119602	0	160	160	0	633136	633136	0

It should be noted that the twice the number rule of thumb was violated in this instance. There were only five DMUs for this region and three variables used for the CRS and VRS models. This brings into question the discriminatory power of the models used. This issue was raised in Chapter 3. Regardless, the analysis was conducted for this study to demonstrate this issue and the consistency of using the geographical regions.

West Africa

The West Africa region consists of six countries. In Table 21, Cameroon (CMR; 1.00) and the Democratic Republic of the Congo (COD; 1.00) were deemed efficient under the CRS model. The other four countries were considered inefficient with a less than one (< 1.00) efficiency score. Conversely, when the VRS model was applied, Cameroon (CMR; 1.00), the Democratic Republic of the Congo (COD; 1.00), and Zimbabwe (ZWE; 1.00) were considered efficient compared to the other remaining countries within this regional group.

Table 21

Phase 2 - West Africa CRS and VRS Efficiency Comparison

West Africa CRS and VRS Efficiency Comparison		
Name	CRS Efficiency	VRS Efficiency
CMR	1.00	1.00
CAF	0.45	0.45
COD	1.00	1.00
MLI	0.86	0.88
NGA	0.27	0.27
ZWE	0.89	1.00

Table 22 is the peer comparison for the West Africa regional countries. In the CRS peer comparisons, Cameroon (CMR) and the Democratic Republic of the Congo (COD) are considered the role models for the other countries in the region. In this analysis, Cameroon (CMR) and the Democratic Republic of the Congo (COD) are peers to all other countries within this region. In the VRS model, Cameroon (CMR), the Democratic Republic of the Congo (COD), and Zimbabwe (ZWE) were evaluated as efficient and became the role models for the remaining countries. These countries could theoretically be considered peers to the remaining inefficient countries.

Table 22

Phase 2 - West Africa CRS and VRS Peer Comparisons

West Africa CRS and VRS Peer Comparison					
	CRS Peers		VRS Peers		
Name	CMR	COD	CMR	COD	ZWE
CMR	✓		✓		
CAF	✓	✓	✓	✓	✓
COD		✓		✓	
MLI	✓	✓	✓	✓	✓
NGA	✓	✓	✓	✓	✓
ZWE	✓	✓			✓

Table 23 shows the slack, target, and percentage comparisons for the West Africa region using the CRS model. There were no recommended changes to the budget or staff variables in the CRS model. However, there is the potential to increase the number of beneficiaries. Both Cameroon (CMR) and the Democratic Republic of the Congo (COD) were considered efficient, and no increase in the number of beneficiaries was observed. Potential increases in the number of beneficiaries could be achieved in the Central African Republic (CAF; 121.97%), Mali (MLI; 15.56%), Nigeria (NGA; 270.05%), and Zimbabwe (ZWE; 11.67%).

Table 23

Phase 2 - West Africa CRS Slack, Targets and Percentage of Change

West Africa CRS Slack and Targets Percentage Comparisons									
Name	Total Budget (I) Value	Total Budget (I) Target	Total Budget (I) Gain(%)	Staff(I) Value	Staff(I) Target	Staff(I) Gain(%)	Beneficiaries(O) Value	Beneficiaries(O) Target	Beneficiaries(O) Gain(%)
CMR	9853016	9853016	0	328	328	0	1352563	1352563	0
CAF	12023162	12023162	0	265	265	0	544041	1207613.67	121.97
COD	28390738	28390738	0	287	287	0	1742327	1742327	0
MLI	5105596	5105596	0	100	100	0	408240	471774.99	15.56
NGA	13090349	13090349	0	220	220	0	294674	1090427.46	270.05
ZWE	996480	996480	0	27	27	0	104398	116580.1	11.67

Table 24 depicts the slack, target, and percentage comparisons for the West Africa region using the VRS model. There were no recommended changes to the budget or staff variables in the VRS model. However, it was observed that there is the potential to increase the number of beneficiaries. Both Cameroon (CMR), the Democratic Republic of the Congo (COD), and Zimbabwe (ZWE) were considered efficient, and no increase in the number of beneficiaries was observed. Potential increases in the number of beneficiaries could be achieved with the Central African Republic (CAF; 121.56%), Mali (MLI; 13.34%), Nigeria (NGA; 268.74%).

Table 24

Phase 2 - West Africa VRS Slack and Target Percentages

West Africa VRS Slack and Targets Percentage Comparisons									
Name	Total Budget (I) Value	Total Budget (I) Target	Total Budget (I) Gain(%)	Staff(I) Value	Staff(I) Target	Staff(I) Gain(%)	Beneficiaries(O) Value	Beneficiaries(O) Target	Beneficiaries(O) Gain(%)
CMR	9853016	9853016	0	328	328	0	1352563	1352563	0
CAF	12023162	12023162	0	265	265	0	544041	1205402.1	121.56
COD	28390738	28390738	0	287	287	0	1742327	1742327	0
MLI	5105596	5105596	0	100	100	0	408240	462712.17	13.34
NGA	13090349	13090349	0	220	220	0	294674	1086595.62	268.74
ZWE	996480	996480	0	27	27	0	104398	104398	0

Regional Summary

Data envelopment analysis (DEA) demonstrates the utility of assessing country portfolios within each region. Due to minimal changes, the West Africa region appears to be the better-performing and managed group. Conversely, the Middle East, East Africa, and Asia have some challenges for resource decisions, conservation of those resources, and the potential to reach a more significant number of beneficiaries within these regional countries.

Phase 3 Evaluation

This phase added the nondiscretionary inputs of the conflict and corruption variables. The budget, staff, and beneficiary variables were used in addition to the corruption and conflict variables. A total of five variables were used to determine the efficiency of the 19 countries in this part of the study.

The comparison is twofold. The first is identifying the efficient countries in relation to all the other countries in this analysis. The second is to determine differences between the constant returns to scale (CRS/CCR) and the variable returns to scale (VRS/BCC) models. All models have an output orientation.

Table 25 is the efficiency comparison between the CRS and VRS models and the nondiscretionary variables of corruption and conflict indices. In the CRS model, Cameroon (1.00), the Democratic Republic of the Congo (1.00), Ukraine (1.00), and Zimbabwe were considered efficient. This equates to roughly 21% of the countries in the aggregate being efficient. Conversely, the VRS model rendered all countries except for the Central African Republic (51.01), Lebanon (22.21), Nigeria (38.72), and Somalia (64.48) as inefficient. This equates to 80% efficiency in the VRS model.

Table 25

Phase 3 - Efficiency Score Comparison Between CRS and VRS Models

Phase 3 Efficiency Score Comparison between CRS and VRS models			
DMU	Description	CRS Efficiency	VRS Efficiency
AFG	Afghanistan	0.79	1.00
CMR	Cameroon	1.00	1.00
CAF	Central African Republic	0.45	0.51
COD	Dem. Republic of Congo	1.00	1.00
ETH	Ethiopia	0.82	1.00
IRQ	Iraq	0.17	1.00
JOR	Jordan	0.07	1.00
LBN	Lebanon	0-.17	0.22
LBY	Libya	0.08	1.00
MLI	Mali	0.88	1.00
NGA	Nigeria	27.23	0.38
PAK	Pakistan	0.89	1.00
SOM	Somalia	0.45	0.64
SSD	South Sudan	0.27	1.00
SDN	Sudan	0.86	1.00
SYR	Syria	0.48	1.00
UKR	Ukraine	1.00	1.00
YEM	Yemen	0.79	1.00
ZWE	Zimbabwe	1.00	1.00

Table 26 depicts the peer comparison of efficient countries and their peers using the CRS model with an output orientation. Peer comparison displays the closest efficient scores compared to those inefficient DMUs. Peer comparisons established a benchmark of the efficient DMUs that can be used as a role model for the inefficient DMUs.

From the CRS models, Cameroon (CMR), the Democratic Republic of Congo (COD), Ukraine (UKR), and Zimbabwe (ZWE) were deemed efficient. Cameroon (CMR) has the preponderance of closest peer comparisons. Conversely, Ukraine (UKR) is a peer unto itself. Finally, Zimbabwe (ZWE) and the Democratic Republic of the Congo (COD) share many of the same peer; 10 and 11 peer countries, respectively.

Table 26

Phase 3 - CRS Peer Comparisons

CRS Peer Comparison					
DMU	Description	CMR	COD	UKR	ZWE
AFG	Afghanistan	✓			✓
CMR	Cameroon	✓			
CAF	Central African Republic	✓	✓		✓
COD	Dem. Republic of Congo		✓		
ETH	Ethiopia	✓			
IRQ	Iraq	✓	✓		
JOR	Jordan	✓	✓		
LBN	Lebanon	✓	✓		✓
LBY	Libya	✓	✓		✓
MLI	Mali	✓	✓		✓
NGA	Nigeria	✓	✓		✓
PAK	Pakistan	✓			✓
SOM	Somalia	✓			✓
SSD	South Sudan	✓	✓		
SDN	Sudan	✓	✓		
SYR	Syria	✓	✓		✓
UKR	Ukraine			✓	
YEM	Yemen	✓	✓		✓
ZWE	Zimbabwe				✓

Table 27 depicts the VRS model peer comparison. In the VRS model, all except four countries were deemed efficient—Central African Republic (CAF), Lebanon (LBN), Nigeria (NGA), and Somalia (SOM). The preponderance of the efficient peer countries was only efficient unto themselves. These countries do not have other peer countries in comparison. However, Ethiopia (ETH) and the Democratic Republic of Congo (COD) have three and four peer countries respectively and are the highest in this comparison.

Table 27

Phase 3 - VRS Peer Comparison

		VRS Peer Comparison														
DMU	Description	AFG	CMR	COD	ETH	IRQ	JOR	LBY	MLI	PAK	SSD	SDN	SYR	UKR	YEM	ZWE
AFG	Afghanistan	✓														
CMR	Cameroon		✓	✓	✓							✓		✓		
CAF	Central African Republic		✓													
COD	Dem. Republic of Congo			✓												
ETH	Ethiopia				✓											
IRQ	Iraq					✓										
JOR	Jordan						✓									
LBN	Lebanon			✓	✓											
LBY	Libya							✓								
MLI	Mali								✓							
NGA	Nigeria			✓	✓									✓	✓	
PAK	Pakistan									✓						
SOM	Somalia	✓										✓				
SSD	South Sudan				✓										✓	
SDN	Sudan										✓					
SYR	Syria												✓			
UKR	Ukraine													✓		
YEM	Yemen														✓	
ZWE	Zimbabwe															✓

Table 28 is the CRS slack and target analysis for all countries using an output orientation. Similar to the phases one and two results, there were no recommended changes to increase or decrease the budgets. The recommended staff reductions were noted in Afghanistan (AFG; -49.14%), Ethiopia (ETH; -32.49%), Pakistan (PAK; -54.54%), and Somalia (SOM; -35.5%). There were no other recommended changes, and the remaining countries remain at the status quo. Because Cameroon (CMR), the Democratic Republic of the Congo (COD), Ukraine (UKR), and Zimbabwe (ZWE) were considered efficient, there were no changes recommended in the beneficiary output. The remaining 15 countries had the potential to increase their beneficiary output. The range of potential increase in the outputs was from Pakistan (PAK; 11.72%) at the minimum to Jordan (JOD; 1199%) at the maximum. Compared to the previous models in phases one and two, these are relatively consistent.

However, the introduction of the conflict variable provided some interesting results. The countries either remained at their current conflict level, or the conflict level was increased. This issue was discussed in Chapters 2 and 3 as a potential concern. An example is Iraq (IRQ), rated at a 10, the maximum score, and indicates a full-war scenario. However, the model recommends a rating of 20.52 or an increase of 105%. This resulting increase is counterintuitive to conflict de-escalation discussed in Chapter 2. Similar results to increase in conflict were also observed in Ethiopia (ETH), Jordan (JOD), Lebanon (LBN), Mali (MLI), South Sudan (SSD), and Sudan (SDN). Because of this scenario, another model was developed to invert the conflict indices, as discussed in Chapters 2 and 3. The new model is discussed later in this chapter.

The observations from the corruption indices remained at the same level or are indicative of correction and improvement. Cameroon (CMR), the Democratic Republic of Congo (COD), Lebanon (LBN), Mali (MLI), Ukraine (UKR), and Zimbabwe (ZWE) all remained the same with no recommended improvement. Recommended country improvement had ranged from a minimum for the Central African Republic (CAF; 26/27.37/5.26%) to a maximum for South Sudan (SSD; 12/53.49/345.75%). The result showed that no countries had regressed or had a worsening corruption index to improve their performance. These results make sense to lessen or minimize the impact of corruptive practices. This is an additional indicator for these countries to take the corrective steps to improve their anti-corruption standings in the future.

Table 28

Phase 3 - CRS Slack and Target Percentages

Phase 3 CRS Slack and Target Percentages															
Name	Budget Value	Budget Target	Budget Gain(%)	Staff Value	Staff Target	Staff Gain(%)	Beneficiaries Value	Beneficiaries Target	Beneficiaries Gain(%)	Conflict Index Value	Conflict Index Target	Conflict Index Gain(%)	Corruption Index Value	Corruption Index Target	Corruption Index Gain(%)
AFG	6717193	6717193	0	430	218.68	-49.14	714542	896217.42	25.43	9	9	0	19	34.2	79.99
CMR	9853016	9853016	0	328	328	0	1352563	1352563	0	7	7	0	25	25	0
CAF	12023162	12023162	0	265	265	0	544041	1203198.89	121.16	8	8	0	26	27.37	5.26
COD	28390738	28390738	0	287	287	0	1742327	1742327	0	8	8	0	18	18	0
ETH	18272611	18272611	0	901	608.28	-32.49	2067873	2508354.55	21.3	8	12.98	62.27	38	46.36	22.01
IRQ	32113081	32113081	0	945	945	0	714542	4002179.62	460.1	10	20.52	105.21	21	71.3	239.51
JOR	31419201	31419201	0	740	740	0	254729	3311289.76	1199.93	5	16.66	233.29	49	54.6	11.43
LBN	24655937	24655937	0	351	351	0	319939	1845760.11	476.91	7	9.08	29.69	25	25	0
LBY	13385797	13385797	0	174	174	0	73975	935729.19	1164.93	10	10	0	17	34.07	100.44
MLI	5105596	5105596	0	100	100	0	408240	459143.05	12.47	6	7.94	32.32	30	30	0
NGA	13090349	13090349	0	220	220	0	294674	1082112.25	267.22	9	9	0	25	30.5	22
PAK	1946603	1946603	0	123	55.92	-54.54	197458	220593.86	11.72	9	9	0	31	35.84	15.63
SOM	12369930	12369930	0	638	411.54	-35.5	770660	1696772.97	120.17	9	9	0	12	32.25	168.72
SSD	24518654	24518654	0	710	710	0	827777	3017991.62	264.59	10	15.46	54.55	12	53.49	345.75
SDN	17815267	17815267	0	408	408	0	1582083	1839598.82	16.28	9	9.23	2.61	16	30.01	87.55
SYR	9547598	9547598	0	284	284	0	579828	1191192.06	105.44	10	10	0	14	37.07	164.78
UKR	1427497	1427497	0	60	60	0	24480	24480	0	9	9	0	33	33	0
YEM	10119602	10119602	0	160	160	0	633136	796276.69	25.77	10	10	0	15	35.88	139.18
ZWE	996480	996480	0	27	27	0	104398	104398	0	6	6	0	24	24	0

Table 29 shows the VRS peer and target results provided minimal changes in the variables observed. This was predominantly due to the maximum number of efficient countries observed in this model. There were only four countries that were not considered efficient in this model—Central African Republic (CAF), Lebanon (LBN), Nigeria (NGA), and Somalia (SOM). The budget variable observed a reduction in both Lebanon (LBN; -18.18%) and Nigeria (NGA; -14.34%). The staff variable reduction was recommended for Somalia (SOM; -20.7%). The increase in beneficiaries was observed in all countries that were not considered efficient. The inefficient countries were the Central African Republic (CAF; 96.04%), Lebanon (350.31%), Nigeria (NGA; 158.25%), and Somalia (SOM; 55.09%). The recommended improvement for the conflict variable was observed only for Lebanon (LBN; 6.52%). Similar to the other observations, the only recommended improvement for the corruption indices was Somalia (SOM; 105.57%).

Table 29

Phase 3 - VRS Slack and Target Percentages

Name	Budget Value	Budget Target	Budget Gain(%)	Staff Value	Staff Target	Staff Gain(%)	Beneficiaries Value	Beneficiaries Target	Beneficiaries Gain(%)	Conflict Index Value	Conflict Index Target	Conflict Index Gain(%)	Corruption Index Value	Corruption Index Target	Corruption Index Gain(%)
Phase 3 VRS Slack and Target Percentages (Aggregate)															
AFG	6717193	6717193	0	430	430	0	714542	714542	0	9	9	0	19	19	0
CMR	9853016	9853016	0	328	328	0	1352563	1352563	0	7	7	0	25	25	0
CAF	12023162	12023162	0	265	265	0	544041	1066544.9	96.04	8	8	0	26	26	0
COD	28390738	28390738	0	287	287	0	1742327	1742327	0	8	8	0	18	18	0
ETH	18272611	18272611	0	901	901	0	2067873	2067873	0	8	8	0	38	38	0
IRQ	32113081	32113081	0	945	945	0	714542	714542	0	10	10	0	21	21	0
JOR	31419201	31419201	0	740	740	0	254729	254729	0	5	5	0	49	49	0
LBN	24655937	20172345	-18.18	351	351	0	319939	1440732.16	350.31	7	7.46	6.52	25	25	0
LBY	13385797	13385797	0	174	174	0	73975	73975	0	10	10	0	17	17	0
MLI	5105596	5105596	0	100	100	0	408240	408240	0	6	6	0	30	30	0
NGA	13090349	11213389	-14.34	220	220	0	294674	760986.49	158.25	9	9	0	25	25	0
PAK	1946603	1946603	0	123	123	0	197458	197458	0	9	9	0	31	31	0
SOM	12369930	12369930	0	638	505.96	-20.7	770660	1195217.27	55.09	9	9	0	12	24.67	105.57
SSD	24518654	24518654	0	710	710	0	827777	827777	0	10	10	0	12	12	0
SDN	17815267	17815267	0	408	408	0	1582083	1582083	0	9	9	0	16	16	0
SYR	9547598	9547598	0	284	284	0	579828	579828	0	10	10	0	14	14	0
UKR	1427497	1427497	0	60	60	0	24480	24480	0	9	9	0	33	33	0
YEM	10119602	10119602	0	160	160	0	633136	633136	0	10	10	0	15	15	0
ZWE	996480	996480	0	27	27	0	104398	104398	0	6	6	0	24	24	0

Because of the irregularities with the phase 3 results compared to phase 1 and phase 2, the phase 3 model was adjusted. The number of efficient countries in the VRS model and the increases in the conflict variable are indicators of these irregularities. Therefore, the conflict variable was adjusted and inverted, as discussed in Chapters 2 and 3. A 1 now represents at war, which was previously a 10. Conversely, at peace is now a 10, which initially was a 1.

Table 30 shows the revised efficiency scores with the conflict variable adjusted. Similar to the CRS model in phase 1, both Cameroon (CMR) and the Democratic of the Congo (COD) were deemed efficient. Additionally, Zimbabwe (ZWE) was efficient in the phase 3 model. The phase 3 model adjusted is an overall 15% efficiency in the aggregate of the evaluated countries. This was slightly improved from the phase 1 aggregate evaluation of 10%. Additionally, comparing the average efficiency scores between phase 1 (51.1) and phase 3 (58.8) averages between the two models showed a slight improvement in the phase 3 model of 7.7 percentage points.

Table 30

Phase 3 - CRS and VRS Efficiency Scores (Conflict Variable Adjusted)

Phase 3 Efficiency Score Comparison between CRS and VRS models (Adjusted Conflict Variable)			
DMU	Description	CRS Efficiency	VRS Efficiency
AFG	Afghanistan	0.77	0.78
CMR	Cameroon	1.00	1.00
CAF	Central African Republic	0.45	0.48
COD	Dem. Republic of Congo	1.00	1.00
ETH	Ethiopia	0.82	1.00
IRQ	Iraq	0.17	0.34
JOR	Jordan	0.07	1.00

Phase 3 Efficiency Score Comparison between CRS and VRS models (Adjusted Conflict Variable)

DMU	Description	CRS Efficiency	VRS Efficiency
LBN	Lebanon	0.17	0.22
LBY	Libya	0.07	0.07
MLI	Mali	0.88	1.00
NGA	Nigeria	0.27	0.27
PAK	Pakistan	0.86	1.00
SOM	Somalia	0.45	0.49
SSD	South Sudan	0.27	0.42
SDN	Sudan	0.86	0.98
SYR	Syria	0.48	0.48
UKR	Ukraine	0.16	1.00
YEM	Yemen	0.78	0.78
ZWE	Zimbabwe	1.00	1.00

In Table 30, the VRS model with the conflict variable adjustment produces eight (42%) efficient countries in this model. In contrast to the phase 1 VRS model, four (21%) countries' efficiency was observed. This is a doubling of efficient countries in the phase 3 VRS model, with the conflict variable being adjusted compared to the CRS model in this instance. The average efficiency score also improved between phase 1 and phase 3 models. The phase 1 VRS model had an average of 59.3%, and the phase 3 VRS model average efficiency improved to 70.3%. This would be an improvement of 11 percentage points in the averages between the phase 1 and phase 3 VRS models.

Table 31 shows the CRS peer comparison with conflict variable adjusted. The preponderance of inefficient peers could theoretically use Cameroon (CMR) as the role model for best practices. Additionally, the Democratic Republic of the Congo (COD) and Zimbabwe (ZWE) are relatively even with several peer-efficient countries in comparison. Finally, several countries could use any efficient countries for best practices. These are the Central African Republic (CAF), Lebanon (LBN), Libya (LBY), Mali (MLI), Nigeria (NGA), and Yemen (YEM).

Table 31

Phase 3 - CRS Peer Comparison (Conflict Variable Adjusted)

CRS Peer Comparison (Adjusted Conflict Variable)				
DMU	Description	CMR	COD	ZWE
AFG	Afghanistan	✓		✓
CMR	Cameroon	✓		
CAF	Central African Republic	✓	✓	✓
COD	Dem. Republic of Congo		✓	
ETH	Ethiopia	✓		
IRQ	Iraq	✓	✓	
JOR	Jordan	✓	✓	
LBN	Lebanon	✓	✓	✓
LBY	Libya	✓	✓	✓
MLI	Mali	✓	✓	✓
NGA	Nigeria	✓	✓	✓
PAK	Pakistan	✓		✓
SOM	Somalia	✓		
SSD	South Sudan	✓	✓	
SDN	Sudan	✓	✓	
SYR	Syria	✓	✓	
UKR	Ukraine	✓		✓
YEM	Yemen	✓	✓	✓
ZWE	Zimbabwe			✓

Table 32 addresses the VRS peer relationship between efficient and nonefficient countries. Cameroon (CMR) has the preponderance of peer-related countries with nine countries. This was followed by the Democratic Republic of the Congo (COD; 8), Ethiopia (ETH; 7), and

Zimbabwe (ZWE; 5), respectively. In addition, several countries are peers to themselves, including Jordan (JOD), Pakistan (PAK), and Ukraine (UKR).

Table 32

Phase 3 - VRS Peer Comparison (Conflict Variable Adjusted)

VRS Peer Comparison (Adjusted Conflict Variable)									
DMU	Description	CMR	COD	ETH	JOR	MLI	PAK	UKR	ZWE
AFG	Afghanistan	✓							✓
CMR	Cameroon	✓							
CAF	Central African Republic	✓	✓	✓		✓			
COD	Dem. Republic of Congo		✓						
ETH	Ethiopia			✓					
IRQ	Iraq			✓					
JOR	Jordan				✓				
LBN	Lebanon	✓	✓	✓		✓			
LBY	Libya	✓	✓						✓
MLI	Mali					✓			
NGA	Nigeria	✓	✓	✓		✓			✓
PAK	Pakistan						✓		
SOM	Somalia	✓		✓					
SSD	South Sudan		✓	✓					
SDN	Sudan	✓	✓	✓					
SYR	Syria	✓	✓						✓
UKR	Ukraine							✓	
YEM	Yemen	✓	✓						✓
ZWE	Zimbabwe								✓

Table 33 is the phase 3 CRS slack and target percentages with conflict variable adjusted. The budget variable remained at the status quo in all cases, with no reductions observed. There were several reductions observed in the staff variable. Namely, Afghanistan (AFG; -48.13%), Ethiopia (ETH; -32.49%), Pakistan (PAK; -53.41%), Somalia (SOM; -35.46%), and Ukraine (UKR; -34.87%) were recommended for staff reduction. Potential improvement was observed to increase the number of beneficiaries from the CRS model results. The efficient countries of Cameroon (CMR), the Democratic Republic of the Congo (COD), and Zimbabwe (ZWE) required no improvement in this area. However, the remaining countries' beneficiaries could increase their beneficiary output. The minimum increase was Mali (MLI;12.47%), while the maximum increase was Jordan (JOD;1199.93%). The adjusted conflict variable demonstrated that the conflict variable was more realistic based on the index ranking. The efficient countries of Cameroon (CMR), the Democratic Republic of the Congo (COD), and Zimbabwe (ZWE) remained at their current index values of 6, 3, and 5, respectively. The other inefficient countries could reduce the level of violence to improve the humanitarian aid to these countries. This was observed in all countries in the CRS model results in Table 33. The corruption index observed recommended improvements in seven of the 19 countries. The remainder of the countries had no change recommendations. The countries that had recommended changes were Jordan (JOD), with a minimal change recommendation. Jordan started with a ranking of 49 and recommended a future rank of 54.6, which was an 11.43% potential improvement (49/54.6/11.43%). Jordan has the highest or least corruption index of countries in this study. The highest recommended change was South Sudan, which started at the lowest corruption index (high corruption perception) with a 12, with recommended improvement towards 53.45, which would be a 345.75% improvement (12/53.49/345.75%).

While several countries did have recommended changes, most other countries did not. For example, Yemen (YEM) is ranked at 15, at the lower end of the corruption index, where a recommended improvement was not observed. There are other similar observations. Most countries did not receive a suggested improvement above the 50-percentile index ranking. For example, only two countries, Jordan (JOD) and Iraq (IRQ), recommended a corruption index score above 50, while the other remained below the 50-percentile ranked score. This requires review and further investigation in the future.

Table 33

Phase 3 - CRS Slack and Target Percentages (Conflict Variable Adjusted)

Phase 3 CRS Slack and Target Percentages (Adjusted Conflict Values)

Name	Budget Value	Budget Target	Budget Gain(%)	Staff Value	Staff Target	Staff Gain(%)	Beneficiaries Value	Beneficiaries Target	Beneficiaries Gain(%)	Conflict Index Value	Conflict Index Target	Conflict Index Gain(%)	Corruption Index Value	Corruption Index Target	Corruption Index Gain(%)
AFG	6717193	6717193	0	430	223.05	-48.13	714542	919144.36	28.63	2	4.49	124.54	19	19	0
CMR	9853016	9853016	0	328	328	0	1352563	1352563	0	6	6	0	25	25	0
CAF	12023162	12023162	0	265	265	0	544041	1203956.47	121.3	3	5.74	91.48	26	26	0
COD	28390738	28390738	0	287	287	0	1742327	1742327	0	3	3	0	18	18	0
ETH	18272611	18272611	0	901	608.28	-32.49	2067873	2508354.55	21.3	3	11.13	270.9	38	46.36	22.01
IRQ	32113081	32113081	0	945	945	0	714542	4002179.62	460.1	1	16.86	1586.26	21	71.3	239.51
JOR	31419201	31419201	0	740	740	0	254729	3311289.76	1199.93	6	12.49	108.18	49	54.6	11.43
LBN	24655937	24655937	0	351	351	0	319939	1845760.11	476.91	4	5.02	25.58	25	25	0
LBY	13385797	13385797	0	174	174	0	73975	945193.25	1177.72	1	3.35	235.37	17	17	0
MLI	5105596	5105596	0	100	100	0	408240	459143.05	12.47	6	6.28	4.74	30	30	0
NGA	13090349	13090349	0	220	220	0	294674	1085160.63	268.26	2	5.24	162.2	25	25	0
PAK	1946603	1946603	0	123	57.31	-53.41	197458	227901.69	15.42	2	6.52	225.88	31	31	0
SOM	12369930	12369930	0	638	411.79	-35.46	770660	1698069.87	120.34	2	7.53	276.63	12	31.39	161.55
SSD	24518654	24518654	0	710	710	0	827777	3017991.62	264.59	1	12.62	1162.47	12	53.49	345.75
SDN	17815267	17815267	0	408	408	0	1582083	1839598.82	16.28	2	6.83	241.54	16	30.01	87.55
SYR	9547598	9547598	0	284	284	0	579828	1199850.9	106.93	1	5.08	407.95	14	21.45	53.19
UKR	1427497	1427497	0	60	39.08	-34.87	24480	151637.61	519.43	2	6.88	244.01	33	33	0

Phase 3 CRS Slack and Target Percentages (Adjusted Conflict Values)

Name	Budget Value	Budget Target	Budget Gain(%)	Staff Value	Staff Target	Staff Gain(%)	Beneficiaries Value	Beneficiaries Target	Beneficiaries Gain(%)	Conflict Index Value	Conflict Index Target	Conflict Index Gain(%)	Corruption Index Value	Corruption Index Target	Corruption Index Gain(%)
YEM	10119602	10119602	0	160	160	0	633136	807848.43	27.59	1	3.11	211.44	15	15	0
ZWE	996480	996480	0	27	27	0	104398	104398	0	5	5	0	24	24	0

Table 34 shows the phase 3 VRS slack and target percentages with conflict variable adjusted. There were budget reductions noted for Iraq (IRQ; -43.1%), Lebanon (LBN; -21.65%), and South Sudan (SSD; -12.64%). No other budget changes were observed in the VRS model. There were several reductions observed in the staff variable. Namely, Afghanistan (AFG; -48.51%), Iraq (IRQ)(-4.66%), and Somalia (SOM)(-21.74%) were recommended for staff reduction. Potential improvement was observed to increase the number of beneficiaries from the VRS model results. The efficient countries of Cameroon (CMR), the Democratic Republic of the Congo (COD), Ethiopia (ETH), Jordan (JOD), Mali (MLI), Pakistan (PAK), Ukraine (UKR), and Zimbabwe (ZWE) required no improvement in this area. However, the remaining countries' beneficiaries could increase their beneficiary output. The minimum was Sudan (SDN, 1.69%) while the maximum was Libya (LBY; 1174.21%) at the maximum potential increase in beneficiary output.

The adjusted conflict variable demonstrated that the conflict variable was more realistic based on the index ranking. The efficient countries of Cameroon (CMR), the Democratic Republic of the Congo (COD), Ethiopia (ETH), Jordan (JOD), Mali (MLI), Pakistan (PAK), Ukraine (UKR), and Zimbabwe (ZWE) remained at their current index values of 6, 3, 3, 6, 6, 2, and 5, respectively. The other inefficient countries could reduce the level of violence to improve the humanitarian aid to these countries. This was observed in all countries in the VRS model results in Table 34.

The corruption index observed recommended improvements in eight of the 19 countries. The remainder of the countries had no change recommendations. The counties that had recommended changes were Libya (LBY), with a minimal change recommendation. Libya started with a ranking of 17 and suggested a future rank of 21.69, which was a 27.56% potential improvement (17/21.69/27.56%). The highest recommended change was South Sudan, which started at the lowest corruption index (high corruption perception) with a 12 and a suggested improvement towards 31.78, which would be a 164.82% improvement (12/31.78/164.82%).

While several countries had recommended changes in their respective corruption index scores, most other countries did not. A country that appears to be on the lower end of the corruption index scale—the Democratic Republic of the Congo (COD) at 18—is an efficient country where a recommended improvement was not observed. There are other similar observations. Additionally, all the countries in the VRS models did not receive a suggested improvement above a 50-index ranking score. This requires review in the future.

Table 34

Phase 3 - VRS Slack and Target Percentages (Conflict Variable Adjusted)

Phase 3 VRS Slack and Target Percentages (Adjusted Conflict Variable)															
Name	Budget Value	Budget Target	Budget Gain(%)	Staff Value	Staff Target	Staff Gain(%)	Beneficiaries Value	Beneficiaries Target	Beneficiaries Gain(%)	Conflict Index Value	Conflict Index Target	Conflict Index Gain(%)	Corruption Index Value	Corruption Index Target	Corruption Index Gain(%)
AFG	6717193	6717193	0	430	221.43	-48.51	714542	910626.73	27.44	2	5.65	182.3	19	24.65	29.72
CMR	9853016	9853016	0	328	328	0	1352563	1352563	0	6	6	0	25	25	0
CAF	12023162	12023162	0	265	265	0	544041	1125242.42	106.83	3	5.31	76.97	26	26	0
COD	28390738	28390738	0	287	287	0	1742327	1742327	0	3	3	0	18	18	0
ETH	18272611	18272611	0	901	901	0	2067873	2067873	0	3	3	0	38	38	0
IRQ	32113081	18272611	-43.1	945	901	-4.66	714542	2067873	189.4	1	3	200	21	38	80.95
JOR	31419201	31419201	0	740	740	0	254729	254729	0	6	6	0	49	49	0
LBN	24655937	19310323.8	-21.68	351	351	0	319939	1438503.75	349.62	4	4	0	25	25	0
LBY	13385797	13385797	0	174	174	0	73975	942596.46	1174.21	1	4.32	331.87	17	21.69	27.56
MLI	5105596	5105596	0	100	100	0	408240	408240	0	6	6	0	30	30	0
NGA	13090349	13090349	0	220	220	0	294674	1064694.84	261.31	2	5.13	156.48	25	25	0
PAK	1946603	1946603	0	123	123	0	197458	197458	0	2	2	0	31	31	0
SOM	12369930	12369930	0	638	499.29	-21.74	770660	1566394.4	103.25	2	5.1	155.16	12	28.89	140.72
SSD	24518654	21420106.5	-12.64	710	710	0	827777	1966603.8	137.58	1	3	200	12	31.78	164.82
SDN	17815267	17815267	0	408	408	0	1582083	1608783.08	1.69	2	4.44	122.06	16	24.66	54.14
SYR	9547598	9547598	0	284	284	0	579828	1198153.26	106.64	1	5.71	471.03	14	24.51	75.07
UKR	1427497	1427497	0	60	60	0	24480	24480	0	2	2	0	33	33	0
YEM	10119602	10119602	0	160	160	0	633136	803618.89	26.93	1	4.69	368.62	15	22.63	50.87
ZWE	996480	996480	0	27	27	0	104398	104398	0	5	5	0	24	24	0

Focus Group

A focus group discussion on DEA was conducted in February 2022. There were three participants in the discussion. All the participants were from academia and were practitioners of DEA. Two themes emerged from the focus group discussion. The first involved the challenges with organizations and their understanding of DEA. The second was from a technical perspective for DEA.

Understanding DEA

"DEA is not a well-known methodology compared to statistics or other quantitative methods" (Participants 2 and 3). Operational researchers, auditors, and economists appear to be the most aware of DEA methodology. DEA has been used for operational research and economics applications. Auditors have applied DEA to understand efficiencies within an organization. Because of the lack of familiarity with the DEA methodology, particularly in the humanitarian sector, basic DEA concepts are needed for a client to understand.

"Homogeneity of DMUs is a broad term" (Participants 2, 3, and 4). The concepts that need to be addressed are homogenous DMUs, variables to be used, and perceptions. DEA should be used to compare similar organizational units. "An example was hospitals. There are for-profit and nonprofit hospitals" (Participant 2). A practitioner of DEA should not mix the two different types of hospitals. There are different rules, regulations, and policies governing the two different types of hospitals. The same can be stated for humanitarian organizations. There are emergency relief and development sustainment types of humanitarian aid operations. This study addresses the latter, and are governed by different rules, regulations and policies. This study focused on the humanitarian sustainment aid operations and was the primary reason for evaluating the efficiency of these countries in the organization.

Another challenge was variable selection. “Variable selection is critical for DEA analysis” (Participant 2). The focus group discussed how variables must be reviewed and scrutinized before a DEA analytical effort. Data or variables provided may be misinterpreted or not aligned to a DEA study. There was often a misunderstanding between the headquarters and the subordinate entity that produced the data (Participant 2, 3, and 4). This was a challenge identified by the participants' previous efforts. If there are data errors from various DMUs, the results may vary significantly (Zhu, 2001). All the participants had commented the need for the data to be free of zeros and that there should be no missing data elements within the data set.

Lastly, the participants had observed from previous DEA efforts that perception is a challenge for an organization. “Some organizations may be reticent to evaluate their organization” (Participant 3 and 4). A client may not want to know how efficient or inefficient their operations may be. A discussion is warranted between the DEA practitioner and a client. A DEA application may provide insights to efficient or inefficient DMUs within an organization; however, it is not a panacea to answer all questions. DEA can point to an area for an organization to conduct additional inquiries or investigations to improve its operational efforts. A participant had commented that initial DEA observations and discussions with a client were “conversation starters” (Participant 3) within an organization. Those organizations that decided to conduct their own internal inquiries discovered their own resource efficiencies, cost savings, and better performance in the end. Participant 3 had commented that the client was initially reluctant to accept the DEA results. However, in reviewing the internal processes and procedures, a considerable savings in resources was achieved with better performance and results. Conversely, “a UN economist was reluctant to accept results from a DEA study simply because the results did not show the UN in a positive way” (Participant 3).

Technical Understanding

The other theme discussed was a DEA from a technical perspective. Since the initial development of the DEA methodology (Charnes et al., 1978), many different DEA applications have developed in the last 44 years. Many of the participants' questions for me were aimed at understanding what DEA processes I was using in the study. Overall, the participants agreed with the study's methodology. However, the participants discussed several techniques that I should consider for follow-up analysis beyond the CRS and VRS modeling conducted in this study. The methods discussed were Malmquist indexing, two stage network analysis, and super efficiency.

"Malmquist indexing would allow for monitoring of DMUs over several observed time periods" (Participants 2 and 3). For example, organizations use Malmquist indexing to determine whether corresponding DMU(s) improvements are being made. This would be ideal from a quarterly or monthly reporting mechanism within an organization, specifically for benchmarking purposes.

The "super efficiency technique would be used to identify those DMUs that are not technically efficient but have a high inefficiency score" (Participant 2 and 3). Super efficiency may assist in determining which inefficient DMUs would need additional monitoring and support compared to those DMUs that are performing well (Zhu, 2001). Super efficiency may be used to assist an organization as a screening tool—for example, whether a DMU efficiency score is 0.90. A super efficiency score of 1.2 may show that the DMU performs well and may not require additional support. Super efficiency may assist in supporting an organization's effort to determine an internal threshold for high functioning performers and those elements that should be reviewed for improvements.

Network analysis is an advanced DEA application. “Network analysis techniques allows for the analysis of each process step to determine the overall efficiency of not only the individual process step, in addition to the entirety of the organizational system” (Participant 4). Two-stage network analysis would entail performing the CRS or VRS models and deriving the efficiency scores. Multi-stage network analysis allows an organization to evaluate two or more critical processes. A humanitarian organization could evaluate how revenue is generated, through fundraising or grant awards, as the first process step. The second process step is training, building capacity, or hiring actions. Lastly, would be how many beneficiaries received services or support during the aid program(s). In each process step, an efficiency score would be an output result. The output of the previous stage one is reintroduced in the second stage as inputs. The result is a performance evaluation that encompasses several levels of efficiency for an organization.

Lastly, the number of DMUs in relation to the number of variables is an important element. “More DMUs is always preferred. By segregating the DMUs into geographic regions, may reduce the discriminatory power of the model” (Participant 4). This is important factor to consider in the design of the analysis in DEA modeling efforts. The rule of thumb becomes and important criteria to consider.

Summary

In summary, the focus group provided valuable insights from the participants' past experiences with organizations and different DEA techniques. The focus group validated the DEA process used in this study in the discussion. The focus group provided examples of the challenges that practitioners may encounter and how they may address an issue to better understand the utility of DEA. DEA can identify best practices that can be replicated in an organization. Conversely, DEA can identify the areas for improvement. However, DEA is not an absolute answer. An additional inquiry would be required for an organization to identify specific areas for process improvement and potential internal policy changes needed to facilitate change.

Chapter 5. Discussion

This chapter summarizes this study in four sections: overview and additional insights, how this study can contribute to nonprofit organizations, limitations of the study, and recommendations for future research.

This study investigated the utility of DEA as a benchmarking application for humanitarian aid organizations, which are under tremendous pressure and competition for donor funds to sustain their operations. As a result, aid organizations and their leaders must adapt to lower costs while improving the quality and delivery of their services. While donor organizations are monitoring the operational and financial goals of nonprofits, the next logical step will be measuring the efficiency and impact of their programs. Additionally, DEA can be viewed as a management instrument to periodically evaluate the efficiency of their operations.

Evaluation of organizational performance is always a complex, multidimensional undertaking. While some components within an organization inevitably perform better than others, for humanitarian aid organizations delivery and reach present unique challenges; not only is the impact of their work potentially a matter of life and death, but the donors funding that work increasingly insist on increased performance metrics.

DEA provides a unique capability to measure the performance of organizational units. However, DEA has rarely been used in the humanitarian sector. DEA can assist leaders in understanding the multidimensional aspects from a performance evaluation perspective or reporting systems. DEA can consider several variables to measure performance and efficiency, which makes DEA an appropriate application. The purpose of this study was to demonstrate the applicability of DEA as a performance system that can evaluate decision-making units and provide insights for a humanitarian organization.

CRS (Charnes et al., 1978) and VRS (Banker et al., 1984) were the two basic DEA models used in this study. Two input variables (budget and staff) and one output variable (beneficiaries) were used in phase one and phase two of this study. Phase one applied both CRS and VRS with all countries being evaluated. Phase two involved the same CRS and VRS models by countries within their geographic region. Finally, phase three introduced the nondiscretionary variables of conflict and corruption in addition to the previously mentioned variables, with the beneficiaries as an output variable.

The process for evaluation remained similar through all three phases. The first was to determine the efficiency scores, peer comparison, and slack and target comparisons. The purpose of the process was to determine whether there were existing conditions or errors. In DEA, it is not enough to determine the efficiency score; additional evaluations of the efficiency scores must consider the peer comparisons, slack, and target comparisons. In the slack and target comparisons, a DEA model can identify the potential areas for improvement.

Findings

Research Question 1

How do the DEA efficiency measures compare and evaluate the organization's country teams in the aggregate and within the organization's regional structure?

Nineteen country portfolios were compared in the aggregate. Both CRS and VRS models were used in the evaluation. The CRS model demonstrated that 10% of the DMUs were efficient. The VRS model showed that 20% of the DMUs were considered efficient in the aggregate. Based on the literature, the CRS model is more restrictive than the VRS model. Thus, the VRS number of efficient countries would have an expected increase compared to the CRS model. Again, this was an expected outcome based on the literature review (Cooper, Seiford, et al., 2011; Medina-Borja, 2002; Banker et al., 1985). Additionally, the relatively low volume of efficiency scores for humanitarian aid organizations was also noted from previous research (Alda & Cuesta, 2019; Martin-Perez & Martin-Cruz, 2017; Medina-Borja & Triantis, 2014). In these case studies, efficient DMUs ranged from 8%–25%. In this study, the DMUs measured had similar observations of 10% (CRS) and 20% (VRS), respectively.

Research Question 2

How do the DEA results of near peer efficiency compare to the organization's efficient vs. inefficient country teams?

The advantage of using DEA is that it can assist management in determining which organizational units are performing well and which others may be underperforming. This becomes an important factor in identifying best practices and replicating those practices to other organizational elements. This is especially important in the nonprofit production effort (Medina-Borja & Triantis, 2014). In this study, the outcome variable was the beneficiaries reached by each country's aid efforts.

In this study, peer comparisons were advantageous to the organization. First, using efficient country portfolio practices, peer comparisons could theoretically be matched with underperforming units. Second, the preponderance of the peer comparisons demonstrated overlap between efficient DMUs and those inefficient peer units. This would allow leadership to decide how to pair efficient and inefficient DMUs. Third, the peer comparisons provided options for management. This study would be to pair country portfolios within their respective geographic regions. This would maintain the leadership oversight with similar practices internal to each geographic region.

Peer comparisons were discussed in Chapter 2 (Emrouznejad & Thanassoulis, 2021; Thanassoulis, 2001), however, the representation of the peer results was not fully realized until the DEA analysis was performed in this study. In DEA, peer comparisons provide an assessment relative to other peers (Thanassoulis, 2001). However, peer comparisons are not absolute. Therefore, the inefficient DMUs should also be reviewing their practices to improve efficiency.

Research Question 3

What areas and level does DEA identify areas for improvement (slack and target values) within the organization's country operations?

DEA slack and target settings were critical in the analysis of this study. Identifying efficient DMUs would not be satisfactory in theoretical or practical applications. The slack and target analyses of the variables demonstrated where resources could be reduced (budget and staff variables) in all phases of the DEA study. Conversely, the modeling depicted potential increases in the numbers of beneficiaries who could be served.

In Chapter 2 slack was discussed and presented with an understanding between the CRS and VRS models and how the output orientation may be represented (Färe et al., 2011; Tone, 2001). However, the target goals were advantageous to understand the scale of change required for each DMU (Emrouznejad & Thanassoulis, 2021; Thanassoulis, 2001) in this study.

In the phase one evaluation comparison with all countries, the CRS model recommended no changes in the budget variable. The VRS model did recommend a reduction in the budget variable for three countries (Iraq, Jordan, and South Sudan). The staffing variable for the CRS model recommended reductions for five countries (Afghanistan, Ethiopia, Pakistan, Somalia, and Ukraine). The reduction of staff ranged from 20.8% to 48%. Similar results were observed in the VRS model (Afghanistan, Iraq, Pakistan, Somalia, and Ukraine). Both the CRS and VRS recommended which DMUs can increase their beneficiary output. The CRS model for beneficiary output ranged from 11.69% to 1199.9%. The VRS model observed potential increases ranging from 1.69% to 1174.21%. See Tables 11 and 12 for the detailed information in Chapter 4.

Similar increases were noted in phase 2. However, the range was less for all three geographic regions. The decrease is due to the number of DMUs observed, which was less within each geographic group than in the aggregate. Additionally, more DMUs were considered efficient among their geographic peers than in the aggregate. This can be attributed to the ratio of DMUs compared to the number of variables, which lessens the model's discriminatory power. See Tables 15, 16, 19, 20, 23, and 24 for detailed information in Chapter 4.

In phase three, there were no recommended changes in the budget variable in the CRS model. However, the CRS model recommended a reduction in the staff variable that ranged from 32.49% to 53.41% for Afghanistan, Ethiopia, Pakistan, Somalia, and Ukraine. Conversely, the VRS model recommended reducing both the budget and staff variables. The budget variable reduction ranged from 12.64% to 43.1% for Iraq, Lebanon, and South Sudan. The staff reduction ranged from 4.66% to 48.51% for Afghanistan, Iraq, and Somalia.

Conversely, observations recommending potential increases in the beneficiaries were noted. For example, the possible number of beneficiaries increased from 12.3% to 1177.72% in the CRS model. The VRS model reported potential beneficiary range increases between 1.69% to 1174%. See Tables 33 and 34 in Chapter 4 for the results and additional information.

While the budget variable is the operating budget expense for the country operations, the budget reduction was not prominent in any phased models. The staff variable where a decrease was noted suggests there may be an issue of congestion (Cooper, Deng, et al., 2011). Lastly, the beneficiary variable reported a potential increase in all phases of the DEA study where the DMU was not deemed efficient. Some extremes were noted that would require additional investigation. The extremes may be due to host-nation limitations on the areas where the organization may or may not operate (e.g., refugee or internally displaced camps only). However, the increase in beneficiaries demonstrates that an organization has more capacity than what was reported in the data set provided.

Research Question 4

Do the external variables of corruption and conflict change the efficiency scores of the organization’s country teams?

There was a minimal difference in the scores when comparing the phase 1 CRS and phase 3 CRS efficiency scores. Cameroon and the Democratic Republic of the Congo were deemed efficient in both CRS models. Six countries (31%) had changed between the two models. Iraq’s phase one CRS efficiency was 0.17, and the phase 3 CRS efficiency score was 0.18. The minimal efficiency changes were noted in Iraq (0.17/0.18), Jordan (0.08/0.07), and Mali (0.88/0.87). The remaining country changes were Pakistan (0.86/0.74), Ukraine (0.16/0.12), and Zimbabwe (0.90/1.00). There was a 68% agreement in phase 1 and phase 3 CRS models.

There was a noticeable change between phase 1 VRS and phase 3 VRS efficiency scores. First, Cameroon, the Democratic Republic of the Congo, Ethiopia, and Zimbabwe were efficient in both VRS models. Additionally, in phase 3, VRS efficiency was also observed for Jordan (0.13/1.00), Mali (0.88/1.00), Pakistan (0.83/1.00), and Ukraine (0.15/1.00). The VRS model provided significant changes for some of these countries. The phase 3 VRS model generated eight of 19 (42%) countries that were considered efficient. This was attributed to the addition of the corruption and conflict variables.

There were minimal changes in the other country observations for the Central African Republic (0.45/0.48) and Lebanon (0.19/0.22). In addition, there were no changes between the phase 1 and phase 3 VRS model for Afghanistan (0.78/0.78), Cameroon (1.00/1.00), the Democratic Republic of the Congo (1.00/1.00), Ethiopia (1.00/1.00), Nigeria (0.27/0.27), Somalia (0.49/0.49), South Sudan (0.42/0.42), Sudan (0.98/0.98), Syria (0.48/0.48), Yemen (0.79/0.79), and Zimbabwe (1.00/1.00). This equated to 57% agreement between both VRS models.

The addition of the conflict and corruption variables influenced the model. This was noted in the increase in the number of countries considered efficient. The corruption variable appeared relatively stable in the phase 3 model for the CRS and VRS comparison. The corruption variable targets either remained the same or were recommended to increase. This observation would be an expected outcome to improve efficiency. The conflict variable observation noted a change to decrease the violence level, which is desirable to improve efficiency. However, the conflict variable was converted because of significant changes in the initial results of the model as discussed in Chapter 4.

As discussed in the Chapter 2 (Cook et al., 2011; Cook & Zhu, 2005; Fried et al., 1999; Banker & Morey, 1986), the introduction of nondiscretionary was performed to determine if there was a change in the efficiency of DMUs. The introduction of the categorical variables does change the outcome for the number of efficient DMUs. Banker and Morey (1986) observed changes in the number of efficient DMUs. Discrete data have an impact on the model. Conversely, Banker and Morey had seen less effect on the number of efficient DMUs when using continuous data. This study attempted to utilize the ordinal rankings to determine whether there was a significant change in the number of DMUs when nondiscretionary variables were introduced to the model.

Research Question 5

What are the potential limitations of performing DEA analysis on humanitarian aid programs and organizations?

There are challenges to using DEA in the humanitarian sector. DEA is not a widely known methodology within the humanitarian sector and has not been widely used to analyze performance and efficiency. There is some reluctance in using DEA because of what the application may discover within an organization.

A limitation of using DEA in this area is the relatively small sample size or the number of DMUs that can be measured. The concept of sample size in relationship to the number of variables was discussed in Chapter 2 (Zhu, 2014; Bowlin, 1998; Banker et al., 1989; Golany & Roll, 1989). Additionally, understanding the concept of homogeneity of sample group of DMUs can be broad, which allows for some flexibility (Emrouznejad & Thanassoulis, 2021). These were discussed in the focus group as potential limitations; however, this can be overcome through discussions with an organization.

Many humanitarian organizations are not large, and therefore a sample size of country portfolios will remain relatively small. A rule-of-thumb construct creates an opportunity for an operational evaluation of an organization. Simply, it would be a challenge for any humanitarian organization to have a sample size conducive to statistical analysis per se. This is not a new phenomenon and has been widely known (Medina-Borja, 2002). In Martin-Perez and Martin Cruz (2017), the data collection was conducted over four years. However, applying an a priori for statistical analysis requirements in the humanitarian sector would also be a challenge. DEA is not a statistical evaluation where minimum sample size is required. This makes DEA a uniquely capable method for evaluating the efficiency of these type of organizations. The rule of thumb—twice the number of DMUs or three times the number of DMUs to the number of variables—provides the DEA's discriminatory power. More DMUs were always a preference for a study in this area. Given that donor contributions and competition for grants have kept many organizations at their current levels, expanding an organization's DMUs is unlikely.

Another challenge is understanding the basic concepts of DEA as an integral part of an organization's operational approach. Defining and understanding what constitutes homogenous units is often a challenge. For example, some organizations have both emergency and longer term development programs. These might seem to be two different sides of the same humanitarian aid coin, but they are vastly different. Emergency operations are short-term by definition, with different operational guidelines. Conversely, developmental efforts are multi-year with varying sets of rules.

Assuming a humanitarian aid organization chooses to implement a DEA effort, the variables need to be carefully considered. There can be no data elements that are missing or have zeros. These errors can be problematic in DEA analysis, due to noise, bias, resulting in a poor model. Clear variable definition and the collection of those variables are critical. This would need to be considered in any DEA effort.

Ancillary to the variable discussion is the weighting of those variables. Ideally, this would require a discussion in conjunction with variable selection. However, from the discussion group, as a matter of practice, weighted and unweighted variables are used to educate management and determine what is believed to be an accurate depiction of the operational context.

Other Findings

Communication and understanding basic DEA concepts are essential for an organization. DEA was not necessarily the solution to an organization's questions or challenges. However, DEA can provide direction and insights on looking for improvements and reducing resource consumption. DEA can highlight where the best and worst practices are occurring within an organization. One should consider DEA as a management tool, no different from statistical analysis, six sigma, project management, or other applications. The advantage of this study demonstrated the efficiency among other peers within an organization. Efficiency is often a nebulous term, which can now be defined through DEA applications.

Super efficiency modeling was discussed in the focus group. Super efficiency is derived when efficient DMU(s) are excluded in this application and evaluates the remaining DMUs' efficiency (Zhu, 2009). Super efficiency would measure the stability of a model due to extremes of inefficient DMUs. This would be akin to addressing outliers in statistical analysis. The super efficiency method's advantage is that there is no need for a priori information because super efficiency increases discrimination without bias or subjectivity within a model. As a result, super efficiency will rank order efficient DMUs (Anderson & Petersen, 1993). However, DEA cannot perform super efficiency models in either CRS or VRS if an input variable is zero. Therefore, all variables should be a positive number; if not, the modeling effort is impractical and not feasible (Lee & Zhu, 2012).

The Malmquist index was out of scope for this study. Although out of scope for this study, the discussion in Chapter 2 (Färe, et al., 2011; Tone, 2004;) and the form the discussion group addresses the potential utility of using the Malmquist Index. This study used a calendar year's performance metrics as the variables. This was due to the limitations of data collection from the organization. However, a Malmquist index application could be performed in the future. Many organizations perform periodic reviews or updates—e.g., monthly or quarterly reports. Applying a Malmquist indexing quarterly would allow an organization to monitor and evaluate the country's portfolios regularly. This would enable the leadership to observe the rise or fall of efficiency over time.

Multi-stage network analysis is a complex method for DEA analysis and evaluation. The outputs of stage one are reintroduced in the second stage as inputs. The result is a performance evaluation that encompasses several levels of efficiency for an organization. For example, Medina-Borja and Triantis (2014) performed a study of a U.S. nonprofit organizations. Their study used a VRS (Banker et al., 1984) model with an output orientation. They had performed a four-stage network analysis that evaluated revenue generation, capacity building, beneficiaries, and consumer satisfaction stages. In their analysis, each output was reintroduced as an input for a follow stage evaluation. Multi-stage network analysis can evaluate an organization holistically on several levels. For example, in Medina-Borja and Triantis (2014), the number of assessed DMUs was approximately 950. Given the organization's size in this study, a two-stage evaluation would be a best-case scenario for a two-stage network approach for evaluating all DMUs in the future.

Limitations

A primary limitation of DEA is that it can be viewed and reported as a lagging indicator(s), which is an observation of past performance. However, benchmarking and reporting, in general, are past performance indicators. Other organizations have shown how DEA could be applied as a part of a selection process. The feasibility of using DEA as part of the selection process for grant rewards could be used in the future. This may be a first step towards efficiency and stewardship of the monies that are provided to humanitarian aid organizations.

The sample size in this study was relatively small. Ideally, a more extensive set of DMUs to evaluate would have been desirable for this study. As discussed earlier, this is a challenge for many humanitarian aid organizations. The primary effort was to determine the efficiency of the organization being studied and the peer comparisons, slack, and potential target areas for improvement. Indeed, applying other techniques and approaches would have been ideal. Second, was to determine the feasibility of using DEA as part of a benchmarking application. The sample size, number of DMUs, in comparison to the number of variables needs to be considered to determine if DEA is feasible for any organization.

Once the efficiency scores have been determined for the organization, the question is, what next? This study does not address this question and should not. This is a question for the leadership in an organization to determine. However, given the efficiency for the organization's scores range from 0.05 to 1.00, the organization would need to address those underperforming elements within the organization. An example would be to leave DMUs with a 0.80 and above alone. In relative terms, these elements are performing well. A super efficiency application may resolve this question. Second, as a practical matter, additional resources to correct well-performing components may not be as productive and financially reasonable. Third, a focus on those elements with an efficiency score of 0.79 and below may need to be address their current operational processes to improve their efficiency. These DMUs are the challenge for overall efficiency within the organization. It is those countries that require support and correction toward efficiency.

Validity

Content and face validity is to understand the degree to which the study construct has been operationalized (Trochim, 2002). The selection of the budget, staff, beneficiary, corruption and conflict variables reflects the operational concerns for the organization and the donors. This can be simplified to the monies spent, develop capacity, and delivery the services to the beneficiaries for humanitarian relief efforts. While aid organizations are operating on a spectrum of conflict or corruptive practices. These are the components that are the operational concerns for an aid organization and their donors. Simply, environment drives the needs of donors to provide humanitarian relief efforts.

The content validity for this study is a check to ensure that the relevant performance measurements are within the construct of this study. The performance criteria were discussed in Chapter 2 and were supported by performance, efficiency, and effectiveness for the non-profit sector (Frederickson, 2003; Werther & Berman, 2001; Light, 2000) Additionally, the donors evaluate humanitarian aid organization on financial and performance based metrics for granting awards and evaluation during and at the of their sponsored programs. The observations from this study were based on DEA theory and the application of CRS and VRS models. In some

It should be restated that the intent of this was to determine the efficiency, peers, slack and targets to management. Second, was to demonstrate the utility of benchmarking the country portfolios. This study has face validity where the measures appear to be valid for performing the above stated requirements (Rubio et al., 2003).

The phase 1 DEA analysis provided the aggregate results and were consistent in the study. The phase 1 analysis was the most meaningful for a humanitarian aid organization. The phase 2 DEA analysis where the country portfolios were separated in their respective geographic regions provided insights on their regional performance. However, the diffusion in the number of DMUs presented its own challenges within these geographic groups. The phase 3 results with the exogenous variables presented unique challenges and how to best to handle the conflict and corruption variables. The first attempt showed that a majority of the DMUs were efficient when the exogenous variable was introduced.

From a subjective perspective, management in the commercial sectors and organizations has supported DEA results' validity. Many commercial and private organizations have employed various DEA techniques. An efficiency score is essentially a management evaluation tool. Therefore, a subjective response from management from a validity perspective may not be convincing or conforming to others from a broader management perspective. However, I relied on my judgment in this research and presented the information objectively (Trochim, 2002).

Recommendations

DEA is a powerful application with myriad adaptations. While this study was focused on the fundamental CRS and VRS models, peer comparisons, slack, and targets, other DEA adaptations could be used in the future. As previously discussed, these could include Malmquist indexing, super efficiency, and possibly two-stage network analysis. Instead of using a calendar year's worth of data, the data could be spread over four reporting quarters. While many organizations provide quarterly reports, a DEA evaluation over each quarter could be performed. Malmquist indexing would allow an organization to monitor the performance over time and compare efficient DMUs accordingly.

In this study, a comparison between the CRS and VRS models was performed. The CRS model inherently constrained the number of DMUs to be efficient, compared to the VRS models. Therefore, I recommend the VRS model for future studies. There was concurrence from the focus group in this recommendation. VRS models allow for more flexibility and encompass variables of all DMUs. Ultimately, the decision would rest with management in determining which model to use. A phase 1 model that measures all country programs in the aggregate would benefit an organization. The number of DMUs to variables will enhance the discriminatory power of a DEA model for identifying efficient programs. This would allow for additional inquiry and replication of best practices in an organization. However, management must be educated on the differences between these models and other DEA applications. Additionally, management should understand the variables, and potential weighting requirements.

Conversely, this study does not recommend the phase 2 analysis of the country portfolios by geographic region. The number of DMUs to the number of variables was not conducive to the discriminatory power of the models in this study. This was demonstrated in Middle East region where the rule of thumb was violated, thus questioning the results. More DMUs to the number of variables is a minimum requirement and desirable. More DMUs are always better.

The evaluation of phase 3 with the addition of nondiscretionary variables is an option. However, the results are inconclusive from a practical perspective. The initial results in Chapter 4 demonstrate that one should be circumspect about how the variables can be used in a model. First, the CRS model would be a recommended model with nondiscretionary variables. The phase 3 CRS model results were more consistent with phase 1 results in the aggregate. Second, based on both the corruption and conflict variables, these country portfolios will continue to be challenged. The countries in this study had a conflict variable in a state of conflict or unrest. The country portfolios conflict variable ranged from a five at the minimum and ten on the highest level. All countries were below the 50th percentile ranking on the corruption scale, which was interpreted that corruption was medium to high on the spectrum. Additionally, it was rare for a target value above the 50th percentile in the corruption index. Lastly, the efficiency scores in some cases varied considerably with the addition of the nondiscretionary variables in the VRS model. An example was Jordan (0.08/1.00). The CRS model results for beneficiary improvement were 1199% recommended increase, consistent with phase 1 modeling results for CRS and VRS models.

Conversely, the phase 3 VRS model target results had not changed, yet Jordan was deemed efficient. This is counterintuitive to the user. Cook and Zhu (2005) demonstrated that a significant change did not occur when exogenous variables were introduced. In this study, this was attributed to the introduction of the corruption and conflict variables. This variation may be the result on how the phase 3 model was defaulted in the software. An output orientation was used on all models for consistency. Because of the output orientation, the nondiscretionary variables resided in the output orientation. This may be the cause and will require further investigation due to this finding.

There was much to be gained from the discussion group. Because DEA is not a well-known quantitative application, the number of experts and practitioners is relatively small. The participants' experience provided valuable insights for this study and other DEA applications that could be applied in the future. Additionally, a novice could learn much from taking a course and having those discussions with the experts and practitioners of DEA.

The primary goals of this study were to demonstrate and test DEA to support humanitarian aid organizations and DEA's multi-faceted ability to measure performance beyond the financial and performance criteria being used today. As humanitarian aid organizations are monitored for financial and operational performance, the demand from donors continues to generate more scrutiny on aid organizations and the stewardship of those resources.

The ultimate objective for aid organizations is to positively impact the communities they serve (Medina-Borja & Triantis, 2014). A DEA evaluation of the DMUs that are the best performing has provided some interesting insights that can be a benchmark toward the effectiveness and efficiency of their aid programs and country operations. The resources being provided to NGOs and nonprofits will need to become more efficient to meet future humanitarian needs.

The sustainable development goals that were adopted by the United Nations are aspirational. However, several banks (African Development Bank et al., 2016) stated that meeting the sustainable development goals will require trillions of dollars in the future. The current funding trends have remained in the billions of dollars, which is unlikely to change in the foreseeable future. Therefore, an additional or alternative means to measure the performance and the efficient utilization of the resources is needed. This study showed that DEA is an application that can be used to measure performance and demonstrate the efficient stewardship of those resources provided to humanitarian aid organizations.

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APPENDIX A

PIM DEA Training

PIM

This is to certify that

Daniel J. Rodman

attended the course

Performance Measurement using Data Envelopment Analysis

Delivered by Performance Improvement Management Ltd
28-29 June 2021

Professor Emmanuel Thanassoulis, Director

PIM

Performance Improvement Management Ltd- C/o
LDP LUCKMANS
1110 ELLIOTT COURT
COVENTRY BUSINESS PARK
HERALD AVENUE
COVENTRY, CV5 6UB.
UNITED KINGDOM

APPENDIX B

Country List and ISO Abbreviations

DMU	Description	Category
AFG	Afghanistan	East Africa/Asia
CMR	Cameroon	West/Central Africa
CAF	Central African Republic	West/Central Africa
COD	Dem. Republic of Congo	West/Central Africa
ETH	Ethiopia	East Africa/Asia
IRQ	Iraq	Middle East
JOR	Jordan	Middle East
LBN	Lebanon	Middle East
LBY	Libya	East Africa/Asia
MLI	Mali	West/Central Africa
NGA	Nigeria	West/Central Africa
PAK	Pakistan	East Africa/Asia
SOM	Somalia	East Africa/Asia
SSD	South Sudan	East Africa/Asia
SDN	Sudan	East Africa/Asia
SYR	Syria	Middle East
UKR	Ukraine	East Africa/Asia
YEM	Yemen	Middle East
ZWE	Zimbabwe	West/Central Africa

APPENDIX C

IRB Approval

Pepperdine University
24255 Pacific Coast Highway
Malibu, CA 90263
TEL: 310-506-4000

NOTICE OF APPROVAL FOR HUMAN RESEARCH

Date: December 14, 2021

Protocol Investigator Name: Dan Rodman

Protocol #: 21-08-1634

Project Title: DATA ENVELOPMENT ANALYSIS AS A BENCHMARKING APPLICATION FOR HUMANITARIAN ORGANIZATIONS

School: Graduate School of Education and Psychology

Dear Dan Rodman:

Thank you for submitting your application for exempt review to Pepperdine University's Institutional Review Board (IRB). We appreciate the work you have done on your proposal. The IRB has reviewed your submitted IRB application and all ancillary materials. Upon review, the IRB has determined that the above entitled project meets the requirements for exemption under the federal regulations 45 CFR 46.101 that govern the protections of human subjects.

Your research must be conducted according to the proposal that was submitted to the IRB. If changes to the approved protocol occur, a revised protocol must be reviewed and approved by the IRB before implementation. For any proposed changes in your research protocol, please submit an amendment to the IRB. Since your study falls under exemption, there is no requirement for continuing IRB review of your project. Please be aware that changes to your protocol may prevent the research from qualifying for exemption from 45 CFR 46.101 and require submission of a new IRB application or other materials to the IRB.

A goal of the IRB is to prevent negative occurrences during any research study. However, despite the best intent, unforeseen circumstances or events may arise during the research. If an unexpected situation or adverse event happens during your investigation, please notify the IRB as soon as possible. We will ask for a complete written explanation of the event and your written response. Other actions also may be required depending on the nature of the event. Details regarding the timeframe in which adverse events must be reported to the IRB and documenting the adverse event can be found in the *Pepperdine University Protection of Human Participants in Research: Policies and Procedures Manual* at community.pepperdine.edu/irb.

Please refer to the protocol number denoted above in all communication or correspondence related to your application and this approval. Should you have additional questions or require clarification of the contents of this letter, please contact the IRB Office. On behalf of the IRB, I wis h you success in this scholarly pursuit.

Sincerely,

Judy Ho, Ph.D., IRB Chair

cc: Mrs. Katy Carr, Assistant Provost for Research