Zakaria Chbani

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PRIORITY REGIONS FOR DEVELOPMENT ASSISTANCE FOR HEALTH: AN EVIDENCE-BASED APPROACH

A THESIS
SUBMITTED TO THE DEPARTMENT OF INDUSTRIAL ENGINEERING
AND THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE
OF ABDULLAH GUL UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
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SCIENTIFIC ETHICS COMPLIANCE

I hereby declare that all information in this document have been obtained in accordance with the academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

Zakaria CHBANI

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M.Sc. thesis titled **"PRIORITY REGIONS FOR DEVELOPMENT ASSISTANCE FOR HEALTH: AN EVIDENCE-BASED APPROACH"** has been prepared in accordance with the Thesis Writing Guidelines of the Abdullah Gül University, Graduate School of Engineering & Science.

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ACCEPTANCE AND APPROVAL

M.Sc. thesis titled **"PRIORITY REGIONS FOR DEVELOPMENT ASSISTANCE FOR HEALTH: AN EVIDENCE-BASED APPROACH"** and prepared by Zakaria CHBANI has been accepted by the jury in the Industrial Engineering Graduate Program at Abdullah Gül University, Graduate School of Engineering & Science.

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Graduate School Dean

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ABSTRACT

PRIORITY REGIONS FOR DEVELOPMENT ASSISTANCE FOR HEALTH: AN EVIDENCE-BASED APPROACH

Zakaria CHBANI

MSc. in Industrial Engineering

Advisor: Assis. Prof. Muhammed SÜTÇÜ

March 2021

Eligibility and allocation criteria of development assistance for health have received much attention in the last years. Critical issues have been raised on the usage of GNI per capita (GNIpc) as a sole indicator for this task. The major critics emphasize the GNIpc overlooks the changes in characteristics of middle-income countries (MICs). These countries now have the highest proportion of poor people and disease burden, combined with significant inequalities. Various alternative frameworks have been suggested that tried to avoid the issues GNIpc failed to take into account. This thesis attempts to build on previous works and introduce a data-driven methodology of developing a framework that guides eligibility and aid allocation decisions. The framework combines health status measures (estimating the level of wellness and illness of a population) and measures of capacity of response to the disease burden. We use Disability Adjusted Life Years (DALYs) as a measure of health status. To determine the measures of capacity, the starting point was to assemble relevant indicators in the literature. Using these indicators, feature selection then allowed to choose a minimal set of discriminative ones. Finally, an aggregate of chosen indicators enables ranking countries by order of priority. Comparing the framework with GNIpc and other frameworks show its potential usefulness. It is better than most other frameworks in targeting countries with a high disease burden and populations in extreme poverty. Moreover, it integrates some concerns other frameworks failed to address.

Keywords: development assistance for health, aid eligibility, allocation criteria, feature selection, inequality

ÖZET

SAĞLIK İÇİN KALKINMA YARDIMINDA ÖNCELİKLİ BÖLGELER: KANITA DAYALI BİR YAKLAŞIM

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Tez Danışmanı: Dr.Öğr.Üyesi Muhammed SÜTÇÜ

Mart 2021

Son yıllarda sağlık alanında kalkınma yardımlarının uygunluğu ve hangi kriterlere göre belirleneceği büyük ilgi görmektedir. Bu alanda yapılan çalışmalarda, kişi başına Gayri Safi Milli Hasıla (GSMH)'nın tek indikatör olarak kullanılmasından dolayı kritik sorunlar ortaya çıkmıştır. Bu konudaki en kritik eleştiri, kişi başına düşen GSMH'nin orta gelirli ülkelerin analizlerinde çok büyük sapmalara sebep olmasıdır. Bu ülkeler önemli dezavantajlara sahip olmakla birlikte en yüksek yoksulluk ve hastalık yüküne sahip ülkelerdir. Kişi başına GSMH'nın hesaba katmadığı bazı alternatif çalışmalar literatürde önerilmiştir. Bu tez, önceki çalışmaları temel alarak, kalkınma yardımlarının uygunluğu ve tahsis kararlarında kullanılan verilere dayalı bir metodoloji sunmaktadır. Bu metodoloji, sağlık durumu ölçütlerini (bir nüfusun sağlık ve hastalık düzeyini tahmin eden) ve hastalık yüküne tepki kapasitesi ölçütlerini birleştirir. Bu çalışmada Yeti Yitimine Ayarlanmış Yaşam Yılı sağlık durumunun bir ölçüsü olarak kullanılmaktadır. Kapasite ölçülerini belirlemek için öncelikli olarak literatürde kullanılan ilgili göstergeleri kapsayan bir gösterge kümesi oluşturulmuştur. Bu gösterge kümesini kullanarak, öznitelik seçimi metodu ile daha küçük ve tanımlayıcı gösterge alt kümesi oluşturulmuştur. Son olarak, seçilen göstergelerin modelde kullanılması ile ülkeler için öncelik sıralamayı elde edilmiştir. Önerilen metodoloji, kişi başına GSMH ve önceki çalışmalarla karşılaştırılarak, önerilen metodolojinin üstünlükleri gösterilmiştir. Önerilen yeni hesaplama metodolojisi “hastalık yükü yüksek ülkeleri” ve “aşırı yoksulluk içindeki nüfusu” hedefleyen diğer birçok metodolojiden daha iyidir. Ayrıca, önerilen metodoloji önceki çalışmalarda ele alınmayan yada çözülemeyen bazı endişeleri de kapsamaktadır.

Anahtar Kelimeler: sağlık için kalkınma yardımı, yardım uygunluğu, tahsis kriterleri, öznitelik seçimi, eşitsizlik

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First and foremost, I would like to thank my advisor Dr. Muhammed Sütçü for his support throughout the period of my master studies, without which none of what is to follow would have been possible.

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My thanks go out to all the students and professors in AGU whom I met and learned from.

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List of Abbreviations

AdaBoost	Adaptive Boosting
ANN	Artificial Neural Networks
CART	Classification and Regression Trees
CLARA	Clustering Large Applications
DAC	Development Assistance Committee
DAH	Development Assistance for Health
DALY	Disability Adjusted Life Year
DALYR_AS	Age-standardized Disability Adjusted Life Year Rate
DIANA	Divisive Analysis
DTP	Diphtheria, Tetanus, Pertussis
EAI	Equitable Access Initiative
GDP	Gross Domestic Product
GHEpc	Government health expenditure per capita
GNIpc	Gross National Income per capita
HALE	Health Adjusted Life Expectancy
HDI	Human Development Index
HIV	Human Immunodeficiency Virus
HIVR	Prevalence of HIV
IHME	Institute of Health Metrics and Evaluation
ILE	Inequality in Life Expectancy
Income40	Income share held by bottom 40%
IQ	Intelligence Quotient
kNN	k-Nearest Neighbors
LE	Life Expectancy
MAR	Missing at Random
MCAR	Missing Completely at Random
MICs	Middle-Income Countries
MDGs	Millennium Development Goals

MMR	Maternal Mortality Ratio
MPL	Multi-Layer Perceptron
NB	Naive Bayes
NCD	Non-Communicable Disease
NIPH	Norwegian Institute of Public Health
OOPP	Out-Of-Pocket Payments
PAM	Partition Around Medoids
PPP	Purchasing Power Parity
RF	Random Forest
SBA	Skilled Birth Attendance rate
SDGs	Sustainable Development Goals
SOM	Self-Organizing Map
SVM	Support Vector Machine
TBR	Tuberculosis Prevalence Rate
THEpc	Total Health Expenditure per capita
U5MR	Under-five mortality rate
U60MR	Under-sixty mortality rate
UNAIDS	United Nations Programme on HIV/AIDS
UNDP	United Nations Development Programme
UNFPA	United Nations Population Fund
UNICEF	United Nations International Children's Emergency Fund
WHO	World Health Organization
YLD	Years Lost due to Disability
YLL	Years of Life Lost

Chapter 1

Introduction

A swift transformation in human health has marked the last 150 years. People in most parts of the world live longer and healthier lives [1]. The enjoyment of the highest attainable health standard is now considered a fundamental right for everyone [2].

Nevertheless, the importance of health cannot be taken separately. Apart from being a right, health is also a means for economic, social, and political development [3,4]. Poor population health conditions among working-age adults reduce labor supply and productivity, thus decreasing economic growth and government revenues. Besides, healthcare consumes resources that could instead be directed to other sectors. The HIV/AIDS pandemic is a pertinent example of these effects. Across Africa, the pandemic has reduced average national growth rates by 2-4% a year [5]. Conversely, improved population health has favorable economic outcomes. A review of historical studies [6] deduced that health improvements in terms of decline in adult mortality in low-income and middle-income countries were responsible for around 11% of economic growth during the period 1960-2000.

Poor health can also deteriorate educational outcomes. Children suffering from infectious diseases, disabilities, and malnutrition, are disposed to reduced school enrollment, increased absenteeism, retardation in cognitive and physical development, and poor school performance. A common health problem found in school-age children in low-income countries is worms. They infect around 169 million children, and due to this, each child loses some 3.75 IQ points. Iron-deficiency anemia is another health condition that touches some 300 million children, costing them around 6 IQ points per child. Hunger is still a significant obstacle to education; some 66 million children go to school hungry. The above health conditions alone translate into an equivalent loss of between 200 million and 500 million days of school in low-income countries each year [7,8].

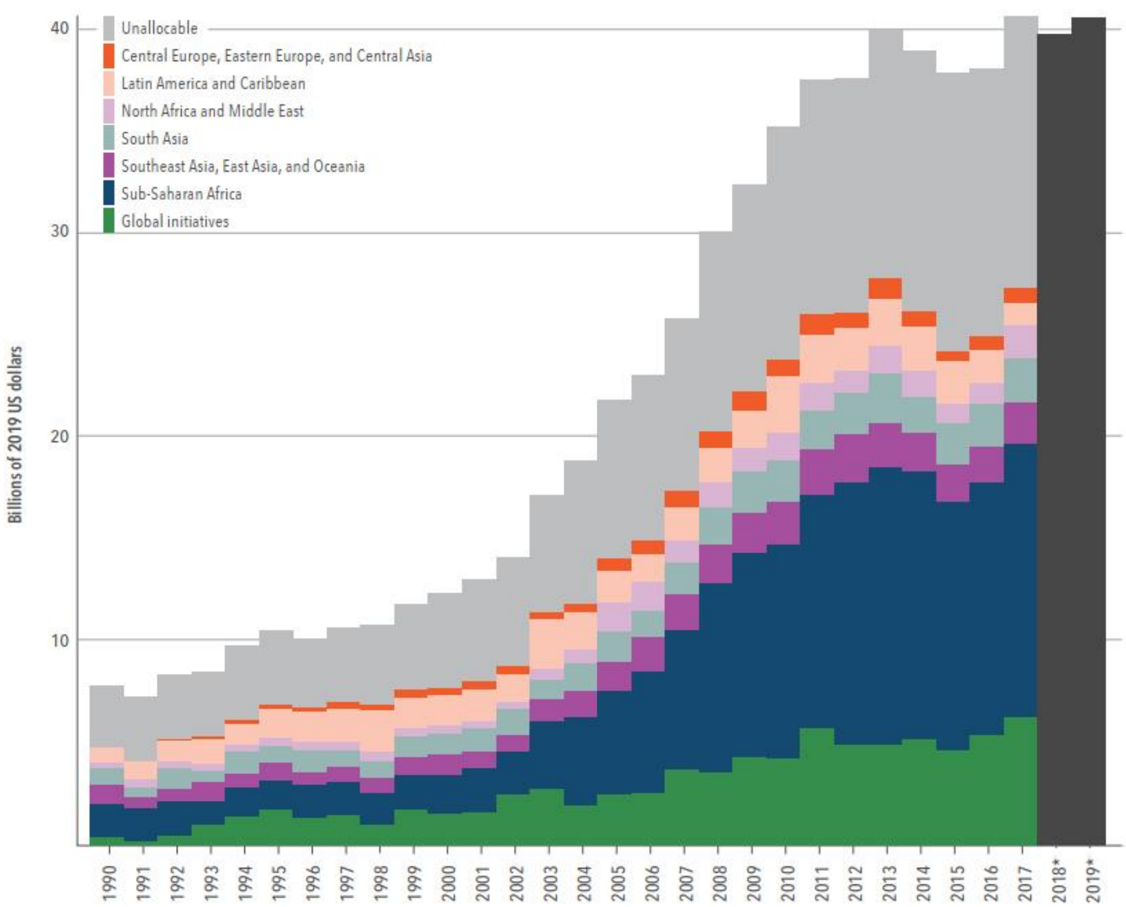
The impact of health goes beyond economic growth and education. The current COVID-19 pandemic is a perceptible example of the extent to which population health can affect the political and social stability of countries, international relations, and many other spheres.

Given its importance, health was central to the Millennium Development Goals (MDGs), an unprecedented commitment by the world's leaders to address the most basic forms of injustice and inequality in our world. Health was expressed in three of the eight MDGs with six targets. Despite a remarkable acceleration towards health targets in many countries since the adoption of the MDGs, the world fell far from meeting health goals by the 2015 deadline [9,10].

The Sustainable Development Goals (SDGs) came in 2015 to tackle the unfinished agenda of the MDGs and extend global agreement and cooperation to other dimensions. Health represented by Goal 3: Ensure healthy lives and promote well-being for all at all ages, acquired more attention with 13 ambitious targets that cover various health matters [11,12]. With ten years left to finish the 2030 SDGs agenda, additional efforts are needed from the global community to reach the defined targets. Many countries may miss several health targets, but more financial resources, cooperation, and better policies could make reaching the targets possible [13]. One instrument that could help accelerate the progress is development assistance for health (DAH). An increase in development assistance and amelioration of its management will support poor countries in providing health services and sustaining their health reform efforts [14].

In 2017, development assistance for health totaled around $41billion, a considerable increase from 2010, when it was $35billion (15.40% percentage change). It made triple the value of $14 billion in 2000 (the year when the Millennium Development Goals (MDGs) were adopted) (Figure 1.1 [15]). DAH accounted for about 27.7% of 2017 health spending in low-income counties. Out-of-pocket spending is, however, more prevailing for health financing in lower-middle-income countries (55.0% of 2017 health spending). Besides, government and prepaid private spending are more relied upon in upper-middle-income and high-income countries (66.9% and 86.0%, respectively) [15] (Table 1.1).

Nevertheless, while their humanitarian peers provide assistance based on assessed needs, development aid actors' decisions are subject to multiple or conflicting objectives [16]. Donor self-interest is a factor that adds to recipient needs and merit for all bilateral donors [17-19]. In a prominent work on this topic in the literature, Alesina and Dollar contend that foreign aid is more governed by political, historical, and strategic determinants than by the recipients' needs. Hoeffler and Outram [19] investigated aid patterns for the five principal members of the Development Assistance Committee (DAC) over the period 1980-2004. The DAC provided 95% of bilateral aid over the given period. The five countries' shares in the total DAC contribution are 24% for the US, Japan (24%), France (12%), Germany (12%), and the UK (5%). All five donors provide more aid to trade partners. The UK and the US, in particular, devote more aid to recipients who vote with them at the UN. France and the UK provide substantial foreign aid to their ex-colonies. Only the UK and Japan provide more aid to countries with higher democracy scores. Moreover, Germany, France, and Japan give more to countries with fewer human rights abuses. Whereas, the US seems to place no importance on recipient merit.



*2018 and 2019 estimates are preliminary

Figure 1.1: Development assistance for health by recipient region, 1990–2019

Table 1.1: Total health spending and health spending by source, 2017 [15]

	Health spending per person (purchasing power parity)	Health spending per gross domestic product	Government health spending per total health spending	Prepaid private spending per total health spending	Out-of-pocket spending per total health spending	Development assistance for health per total health spending
Total	1,418	9.7%	60.7%	20.6%	18.5%	0.50%
High-income	5,825	12.2%	62.8%	23.2%	14.0%	0.00%
Upper-middle-income	1,053	5.7%	56.5%	10.4%	32.9%	0.20%
Lower-middle-income	289	3.9%	32.7%	8.9%	55.0%	3.50%
Low-income	119	5.3%	25.0%	5.9%	41.4%	27.7%

Chapter 1 represented a concise introduction to the importance of health and development assistance for health and to the biases that can intervene with its allocation, mainly for bilateral donors. Chapter 2 discusses the Gross National Income per capita (GNIpc) as a “more objective” criterion for aid eligibility and allocation adopted mainly by major multilateral donors, its limitations, and the frameworks proposed as an alternative to GNIpc. The chapter also states the problem our study is dealing with and our project’s objectives. Chapter 3 shows the methodology developed in this research to construct a new framework that we contend it represents a fairer alternative to GNIpc. Chapter 4 reveals our analysis results and presents a comparison of the framework with other frameworks in the literature. Our conclusions are drawn in the last chapter.

Chapter 2

Related works

Major multilateral development aid entities rely mainly on Gross National Income per capita (GNIpc) for determination of aid eligibility and allocation [20]. This indicator has shown, however, severe limitations. Health is a multidimensional issue, and while GNIpc measures average national accounts, it does not capture the health needs and well-being of people, nor the existing inequalities [21]. Besides, GNIpc penalizes middle-income countries (MICs) which currently have the highest proportion of poor people (mainly due to higher inequality in income distribution) [22]. Coupled with this is the current transition in disease burden in middle-income countries with the rise of non-communicable diseases (NCDs) [23,24]. MICs are not only exposed to receiving less aid than reflected by their needs but are indeed at risk of losing eligibility as they attain a GNIpc that excludes them from receiving assistance. Over a dozen of MICs are likely to surpass eligibility thresholds in the few coming years. These countries are on average in weaker macroeconomic conditions, with more vulnerable health systems, and with higher poverty and inequality than the group of countries that graduated previously [25] (Figure 2.1). These limitations raise an urgent question as to whether GNIpc should continue to dictate decisions about eligibility and allocation of development assistance for health.

The Equitable Access Initiative (EAI) [26] launched in 2015 was a groundbreaking effort in research for alternatives to GNIpc. Nine multilateral actors were behind the initiative: Gavi, the Global Fund, UNAIDS, UNDP, UNFPA, UNICEF, Unitaid, the World Bank and WHO, together with high-level experts. The conveners of the initiative assigned the task of developing potential alternative frameworks to four expert academic teams representing: The University of Oxford, the Institute of Health Metrics and Evaluation (University of Washington), the University of Sheffield/Imperial College, and the Norwegian Institute of Public Health (NIPH). The final report of each team can be accessed from [27]. The methods and findings of the NIPH were summarized in [28].

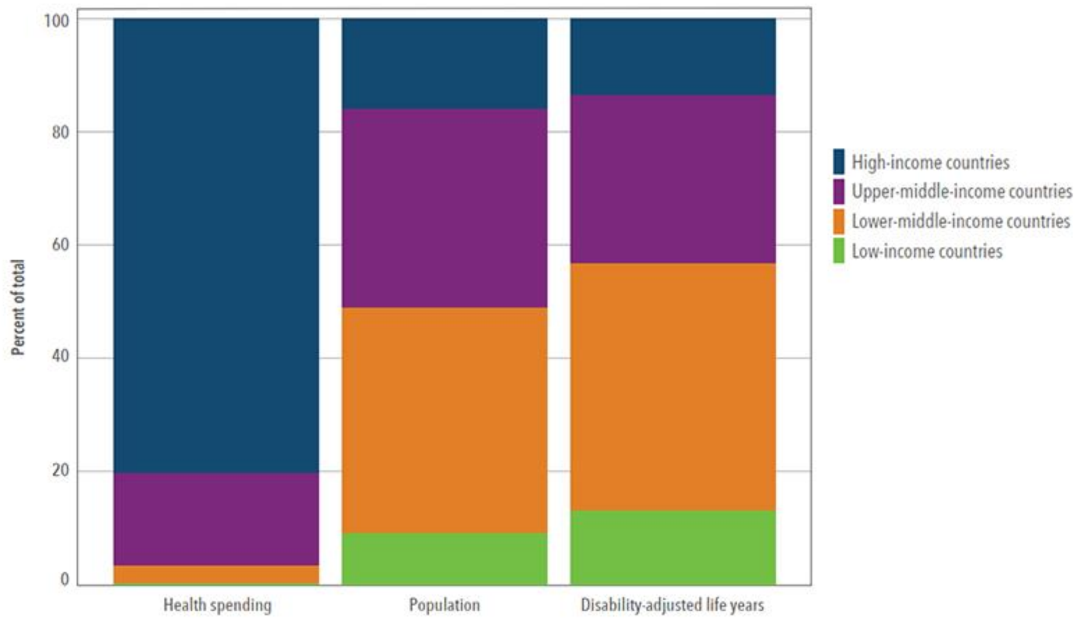


Figure 2.1: Health spending, population, and disability-adjusted life years by World bank income group, 2017 [15]

The teams agreed that a multi-criteria framework that moves beyond income levels by considering health needs, inequality in income, as well as domestic capacity and policies, should inform external health financing decisions. Furthermore, the teams proposed that a continuous arrangement framework should be used rather than discrete groupings of countries that make a country ineligible for support once it surpasses a specific GNI per capita threshold.

Nevertheless, works of the teams resulted in broadly different frameworks. The Norwegian Institute of Public Health examined 27 distinct multi-aggregate measures (e.g., average of normalized GNIpc and Life expectancy). The University of Oxford proposed five frameworks (e.g., GNI adjusted with Gini index: GNIpc*(1 – Gini)). The team representing the University of Sheffield/Imperial College introduced three composite indices. Whereas, the Institute of Health Metrics and Evaluation approach handled health goals distinctively by measuring the gap between resources needed to reach a specific goal, a country's government expected spending, and a country's potential government spending (Table 2.1).

Table 2.1: Frameworks proposed by the Equitable Access Initiative

Team	Frameworks	Missing *
Oxford University	GNI adjustment with GINI index: GNIpc(1 – Gini)	69
	GNI adjustment with Income share of bottom 40%: GNIpc(1 – Income40)	69
	GNI adjustment with Disability-Adjusted Life Years: GNIpc(1 – DALY)	9
	GNI adjustment with Health Adjusted Life Expectancy: GNIpc*HALE	8
	GNI adjustment with Strict Index (proposed by Sheffield): GNIpc*Strict index	11
IHME	Gap between resources need (N) and government's expected spending (ES)	-
	Gap between resources need (N) and a country's potential government spending relative to peers (PS)	-
NIPH	Average of normalized GNIpc and Under-five mortality rate (U5MR)	6
	Average of normalized GNIpc and Under-sixty mortality rate (U60MR)	9
	Average of normalized GNIpc and Life expectancy (LE)	8
	Average of normalized GNIpc and Healthy life expectancy (HALE)	8
	Average of normalized GNIpc and Disability-adjusted life year rate (DALYR)	9
	Average of normalized GNIpc and Age-standardized disability-adjusted life year rate (DALYR_AS)	9
	Average of normalized GNIpc and Debt service (% of GNI) (Debt)	70
	Average of normalized GNIpc and Tax revenue (% of GDP) (Tax)	44
	Average of normalized GNIpc and Total health expenditure per capita (THEpc)	8
	Average of normalized GNIpc and Government health expenditure per capita (GHEpc)	5
	Average of normalized GNIpc and Absolute improvement in under-five mortality rate (cU5MR)	5
	Average of normalized GNIpc and Relative improvement in under-five mortality rate (rcU5MR)	5

NIPH	Average of normalized GNIpc and Absolute improvement in skilled birth attendance rate (cSBA)	75
	Average of normalized GNIpc and Relative improvement in skilled birth attendance rate (rcSBA)	75
	Average of normalized GNIpc and Maternal mortality ratio (per 100,000 live births) (MMR)	10
	Average of normalized GNIpc and Prevalence of HIV (% of population ages 15-49) (HIVR)	56
	Average of normalized GNIpc and Tuberculosis prevalence rate (per 100,000 population) (TBR)	5
	Average of normalized GNIpc and Inequality in life expectancy (ILE)	5
	Average of normalized GNIpc and Gini index for income (Gini)	69
	Average of normalized GNIpc and Income share held by bottom 40% (% of total income) (Income40)	69
	Average of normalized GNIpc and Skilled birth attendance rate (% of total deliveries) (SBA)	27
	Average of normalized GNIpc and Coverage of three doses of vaccine against diphtheria, tetanus, and pertussis (% of children aged 12–23 months) (DTP3)	6
	Out-of-pocket payments (% of total health expenditure) (OOPP)	7
	LE, ILE and SBA with equal weights (MCF_EQ LE baseline)	18
	LE, ILE and SBA with weights informed by online survey (MCF_SU LE baseline)	18
	GNI, ILE and SBA with equal weights (MCF_EQ GNI baseline)	22
	GNI, ILE and SBA with weights informed by online survey (MCF_SU GNI baseline)	22
Sheffield univ. & Imp. College of London	Strict health development index: $\sqrt{a * b}$ $a = \frac{\sqrt{ind1 * ind2}}{\max\,(geo\ mean(1,2))}$ ind1: min-max normalization of skilled birth attendance (%) ind2: min-max normalization of inverse of total DALYs lost b: min-max normalization of pooled health expenditure (% total health expenditure)	7

	Extended health development index: $\sqrt[3]{a * b * c}$ $c = \frac{\sqrt{ind4 * ind5}}{\max\ (geo\ mean(4{,}5))}$ ind4: min-max normalization of GNI per capita (USD PPP) ind5: min-max normalization of Tax revenue (% GDP)	48
	"Strict + fiscal" health development index: $\sqrt[3]{a * b * d}$ $d = \frac{\sqrt[3]{ind5 * ind6 * ind7}}{\max\ (geo\ mean(5{,}6{,}7))}$ ind6: min-max normalization of Government expenditure on health (% total government expenditure) ind7: min-max normalization of inverse of Total debt service (% GNI)	97

* Missing values for the year 2016 after imputation using the procedure in 3.3.2

The ranks generated with the frameworks differed markedly from those based on GNI and shared relatively common directions of change. However, the changes in ranks from one to another framework were significant. In the end, the EAI report did not recommend any specific framework.

Apart from this, while the EAI emphasized the importance of inequalities, measures of inequality were not incorporated in most of the proposed frameworks contending a lack of satisfactory quality data. The availability of data was a severe limitation for some other frameworks as well, restraining their utility.

We realized in this chapter the limitations of GNIpc as a criterion for aid eligibility and allocation. We have also seen frameworks suggested as alternatives to GNIpc and their shortcomings. Considering the requirements that the existing frameworks failed to fulfill and motivated by bringing more fairness and objectivity to the process, we aim in this study to apply a different approach for dealing with the problem in which we introduce a new framework derived from probative data. Based on this, the framework has to follow the following requirements:

- To be quite comprehensive of different dimensions of the problem.
- To be based more on evidence from data than on dispersed propositions of experts.
- To avoid pitfalls and limitations of previous works.

- To constitute an aggregate of indicators as simple as possible for decision-makers with available and timely indicators.

This study responds to a growing debate in the literature about delivering development assistance for health. Even though we do not guarantee the resulting framework is worth considering as a better alternative to GNIpc or other frameworks, we consider our main contribution to state of the art is to offer a new perspective that may boost the discussion on this topic.

Chapter 3

Methodology

Our approach focuses on incorporating two principal dimensions for assessing a country's need for development assistance for health: the burden of disease, and the capacity of response.

3.1 Measuring the burden of disease

To measure the burden of disease, we choose the Disability Adjusted Life Years (DALYs). The advantage of this measure manifests in its combination of information about mortality and morbidity in a single number. "Conceptually, one DALY is the equivalent of losing one year in good health because of either premature death or disease or disability" [29]. "The sum of these DALYs across the population, or the burden of disease, can be thought of as a measurement of the gap between current health status and an ideal health situation where the entire population lives to a late age, free of disease and disability.

DALYs for a disease or health condition are calculated as the sum of the Years of Life Lost (YLL) due to premature mortality in the population and the Years Lost due to Disability (YLD) for people living with the health condition or its consequences" [30]:

DALY = YLL+ YLD

YLL = N x L

where:

N = number of deaths

L = standard life expectancy at age of death in years

YLD = P x DW

where:

P = number of prevalent cases

DW = disability weight

The DALYs are provided for three categories: non-communicable diseases (NCDs); communicable, maternal, neonatal, and nutritional diseases; and injuries [29].

In our analysis, we consider DALYs rates related only to communicable and non-communicable diseases. Injuries, on the other hand, cover not only accidents, but also natural disasters and violence, including interpersonal violence, conflict, and terrorism [29]. These incidents are primarily subject to humanitarian and not development assistance.

DALYs' crude rates will favor countries having large old populations that naturally have a high contribution to the disease burden due to ageing-related diseases and high mortality. For this reason, we use age-standardized DALYs rates that take into consideration demographic structure differences between populations.

Figures 3.1 to 3.3 present age-standardized DALYs per 100,000 people for the three categories of DALYs across countries for the year 2016. There is a notably high burden of communicable diseases in Sub-Saharan Africa and South Asia. Rates for non-communicable diseases and injuries are more scattered and prevalent in more developed regions as well. Western Europe, Australia, Japan, and Canada, in contrast, have lower rates for the three categories.

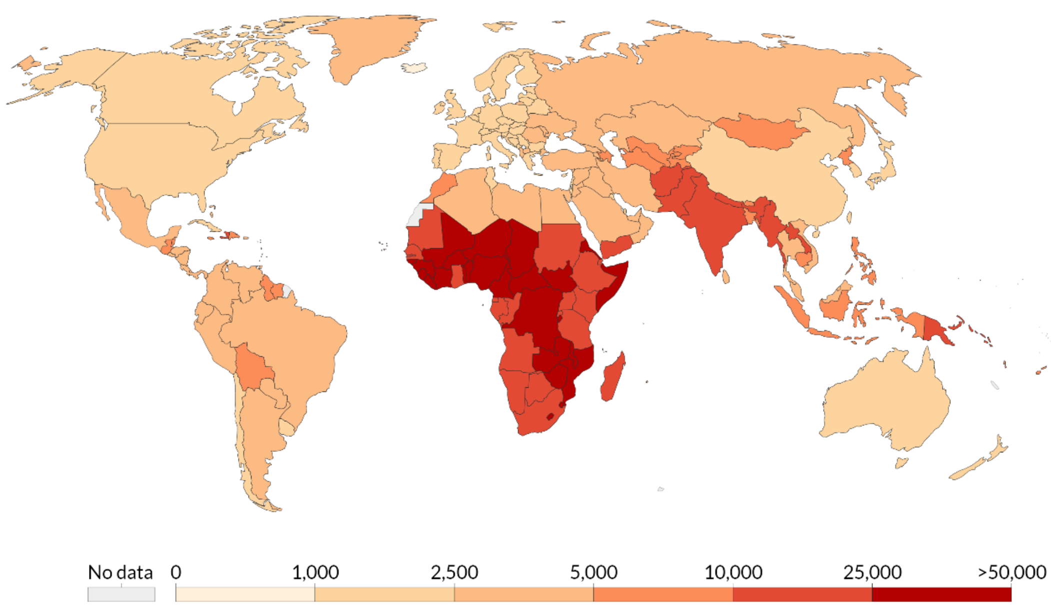


Figure 3.1: DALY rates from communicable, neonatal, maternal & nutritional diseases, 2016

Source: IHME, Global Burden of Disease [31].

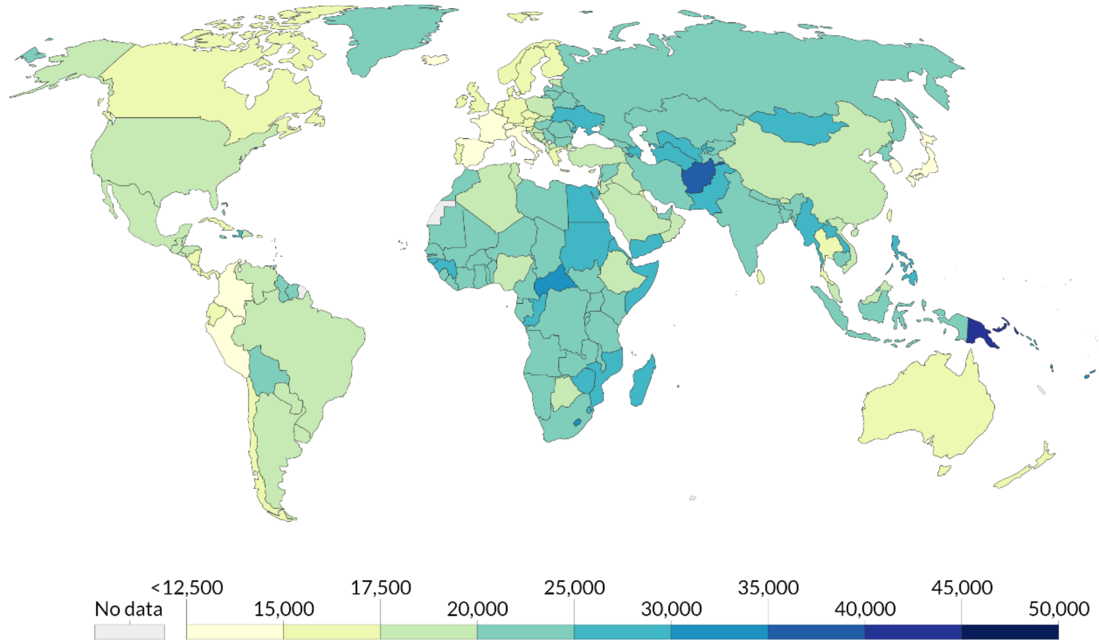


Figure 3.2: DALY rates from non-communicable diseases (NCDs), 2016

Source: IHME, Global Burden of Disease [31].

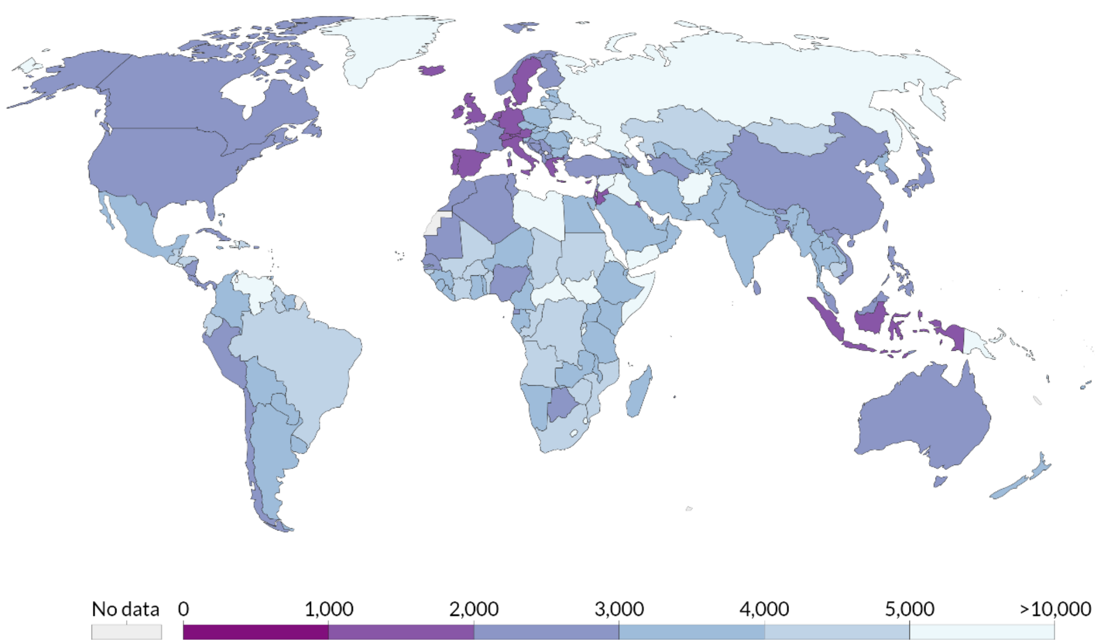


Figure 3.3: DALY rates from injuries, 2016

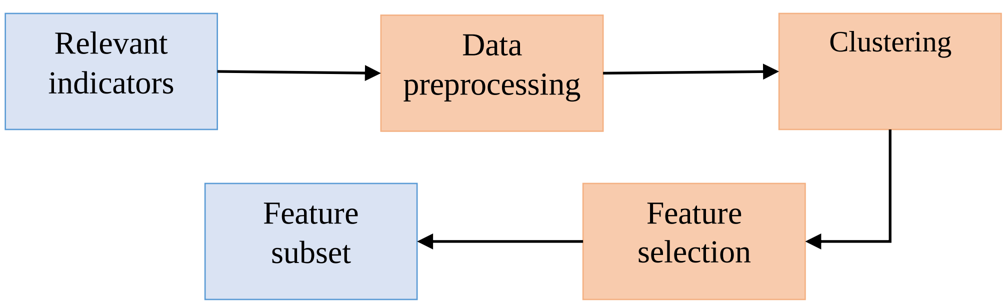
Source: IHME, Global Burden of Disease [31].

3.2 Measuring the capacity of response

A large number of factors are studied in the literature. Including all these factors for making a decision is not feasible. A limited number of factors that prove to be relevant can only be incorporated. For this purpose, we start with a broad set of indicators that gained interest in the literature, including ones the panel of experts of the Equitable Access Initiative has employed. Table 3.1 lists the chosen indicators and sources proving their relevance. We then go on an analysis to determine a small subset of these features to integrate into our framework.

Together with the burden of disease and the capacity of response dimensions, we count for the dynamic nature of the burden of disease by including three indicators for the incidence of three major health threats: HIV, tuberculosis, and malaria (see Table 3.1). The three indicators are also included in the search for the feature subset.

The search for a feature subset is carried as below, extended details of each step are given in the following parts:



We preprocess data of the initial indicators to improve their quality, then normalize the indicators' values. This task is necessary so that we can obtain high-quality clustering of countries. We cluster the countries using all the indicators so that we have countries with closer values for different indicators at the same cluster. For instance, in one of the clusters, we may have countries with the best levels for different health dimensions, and in another cluster, countries with the worst values for different indicators. The resulting clusters allow us to assign group labels that will constitute a new characteristic variable of countries instances. These labels will guide feature selection to find a small feature subset that conserves, to the best possible, the grouping of countries the clustering led to. An indicator that is part of an optimal subset is an indicator that has useful information about the countries grouping. Finally, as we will see later, feature selection generates many and not one optimal subset. We make use of this in assigning weights to the indicators that we will include in the final aggregate used to calculate the countries' scores. These scores will serve to rank the countries by order of priority. By following this approach, we will be able to include all the indicators implicitly while using only a limited number of them in our calculations.

3.3 Data

3.3.1 Data sources

We use four main sources of quantitative data. Data were mainly extracted from the World Bank development data [32]. Data related to the burden of disease were derived from the Global Burden of Disease datasets [31]. While data regarding the Human Development were obtained from [33] and [34].

3.3.2 Data cleaning

Not all countries and indicators have complete data. For this reason, we use the year 2016 as a baseline, as it is the most recent year with less missing values, and impute the missing values using data for the ten last available years (2008-17). The Little's MCAR test shows that data are missing at random (MAR).

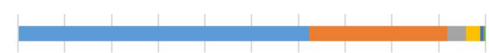
For an indicator with missing values, we proceed as the following:

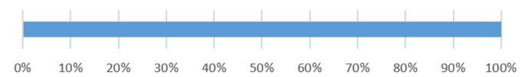
- We take complete cases for the ten years, delete the values for the baseline year (2016), build several models on each time series to predict the value for the year 2016 (linear regression, exponential smoothing with linear, multiplicative, and without trend). The method with the least sum of error for all complete cases is chosen to fill the missing values for the other cases of the given indicator.
- If there are no data points enough for interpolation or extrapolation, we use the same values as the nearest years as long as the values are from the three nearest years.
- If there is no data point for particular countries or data date to more than three years, the value is left missing.

The proportion of values for each imputation method are presented in Table 3.1. After imputation, the indicators are scaled using a min-max normalization so that they are in the same [0,1] range.

Table 3.1: List of indicators

Indicator	Sources for relevance	Median	Data completeness
Births attended by skilled health staff (% of total)	SDG 3.1.2, MDG 5.2, [35], NIPH, Sheffield	97.97	
Current health expenditure per capita, PPP (current international $)	SDG 1.a, [35], NIPH	767.77	
Domestic general government health expenditure per capita, PPP (current international $)	SDG 1.a.2, [35], NIPH	373.11	
GINI index (World Bank estimate)	SDG 10.1, MDG 1.A, NIPH, Oxford	36.70	
GNI per capita, PPP (current international $)	SDG 8.1, HDI, MDG 1.B, NIPH, Oxford, Sheffield	12150	
Hospital beds (per 1,000 people)	SDG 3.8.1, [35]	2.8	
Immunization, DPT (% of children ages 12-23 months)	SDG 3.b.1, [35], NIPH, [36]	93.5	
Incidence of HIV (per 1,000 uninfected population ages 15-49)	SDG 3.3.1, MDG 6.1, [35], NIPH	0.2	

Incidence of malaria (per 1,000 population at risk) [1]	SDG 3.3.3, MDG 6.6, [35]	0	
Incidence of tuberculosis (per 100,000 people)	SDG 3.3.2, MDG 6.9, [35], NIPH	48.5	
Income share held by lowest 40%	SDG 10.1.1, MDG 1.A, NIPH, Oxford	18.27	
Nurses and midwives (per 1,000 people)	SDG 3.c.1, [35,36]	2.91	
Out-of-pocket expenditure (% of current health expenditure)	SDG 3.8.2, [35], NIPH, Sheffield, [36]	31.17	
People using at least basic drinking water services (% of population)	SDG 1.4.1, SDG 6.1, MDG 7.8, [35]	95.61	
People using at least basic sanitation services (% of population)	SDG 1.4.1 & 6.2, MDG 7.9, [35,36]	88.73	
Physicians (per 1,000 people)	SDG 3.c.1, [35,36]	1.41	
Poverty gap at $1.90 a day (2011 PPP) (%)	SDG 1.1, MDG 1.A	0.5	
Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population)	SDG 1.1.1, MDG 1.A	1.4	
Tax revenue (% of GDP)	SDG 17.1.2, NIPH, Sheffield	16.25	

Total debt service (% of GNI)	SDG 17.4, MDG 8.12, NIPH, Sheffield	3.57	
Mean years of schooling (years)	SDG 4.1 & 4.3, MDG 2, HDI	8.9	

■ 2016 value ■ Interpolated/Extrapolated ■ Not imputed ■ 2015 or 2017 value ■ 2014 value ■ 2013 value

[1] Missing values were turned to zero value as they correspond to countries outside malaria prevalence regions.
NIPH: Norwegian Institute of Public Health report; Oxford: University of Oxford report; Sheffield: University of Sheffield/Imperial College report.

3.4 Grouping of countries

The indicators listed previously may all be considered relevant. We may not tell if an indicator proposed by an expert is better than one nominated by another expert. Conversely, considering all these indicators, we can be more confident that we covered most of the essential dimensions of the problem. A clustering of countries using these indicators may be an appropriate depiction for the grouping of countries we want, given that countries that have close values for different indicators are likely to be in the same cluster. Then, feature selection comes to find a small set of indicators that conveys much the same that grouping.

Even after imputation, we still have missing data. So, we go for clustering using the Batch k-means as it allows performing clustering with incomplete data. “The k-means algorithm is a simple iterative method to partition a given dataset into a user-specified number of clusters, k” [37]. The k-means procedure is summarized in Algorithm 3.1 [38].

For being more assured using k-means, we do a comparison experiment: We fill the remaining missing data using 3-NN (k-nearest neighbors with k=3), then evaluate k-means and other clustering algorithms for compactness, separation, and connectedness with 4 clusters and 5 clusters. The algorithms comprised in the experiment are k-means, DIANA, PAM, Model-based clustering, SOM, and CLARA. The validation measures are Dunn index [39], Silhouette Width [40], and Connectivity [41]. Higher values for Dunn index and Silhouette Width are preferred, while lower values for Connectivity are favored.

Algorithm 3.1: The k-means algorithm

Input:
k: the number of clusters,
D: a data set containing n objects.

Output: A set of k clusters.

Method:
(1) arbitrarily choose k objects from D as the initial cluster centers;
(2) repeat
(3) (re)assign each object to the cluster to which the object is closer based on the mean value of the objects in the cluster;
(4) update the cluster means, that is, calculate the mean value of the objects for each cluster;
(5) until no change;

K-means topped the rank for Silhouette and connectivity measures, while DIANA scored the highest value for Dunn Index. Meanwhile, Model-based clustering was the worst. With k-means, a grouping of 4 gives better values for the three measures than a grouping of 5 (Table 3.2). Besides, a clustering of 4 allows the comparison with the Human Development Index (HDI) groups, for which we expect considerable correspondence as the HDI holds strong support as a measure of the overall development of a country. Given these points, a k=4 Batch k-means clustering is performed with incomplete data for our analysis.

Table 3.2: Clustering algorithms comparison

		k=4	k=5
k-means	Connectivity	54.38	65.22
	Dunn	0.14	0.14
	Silhouette	0.28	0.23
DIANA	Connectivity	66.47	68.16
	Dunn	0.15	0.16
	Silhouette	0.22	0.22
SOM	Connectivity	68.80	80.13
	Dunn	0.11	0.11
	Silhouette	0.22	0.18
Model	Connectivity	99.06	131.06

	Dunn	0.11	0.08
	Silhouette	0.17	0.10
PAM	Connectivity	84.25	99.62
	Dunn	0.13	0.15
	Silhouette	0.18	0.17
CLARA	Connectivity	73.54	88.91
	Dunn	0.10	0.11
	Silhouette	0.18	0.17

3.5 Feature selection

The intent of using feature selection is to nominate a narrow subset of initial indicators that conveys a grouping of countries much the same one resulting from the clustering phase. Finding this subset of features is done by eliminating redundant indicators and less relevant ones.

Two dominant approaches are used for feature selection: filters and wrappers [42]. Filter methods rank the features by scores that are assigned to each feature using a statistical measure. The statistical measure can be intrinsic to the feature or characterizes the feature's relation with the class attribute. The features having a high rank are thus selected. For wrapper methods, a feature subset selection algorithm starts a search for a proper subset of features; the subset is then evaluated by a classifier and compared to previous combinations of features to find the combination that maximizes the performance of the model (Figure 3.4 [43]).

Filter methods are computationally efficient, thus useful for datasets with a considerable number of features. Also, they are independent of the classification algorithm. It results that feature selection needs to be done only once. A downside of filter methods is that they generally ignore feature dependencies, as they evaluate each feature separately. As a result, redundant features may still be selected. Another critical drawback of filters is that the selection criterion is not directly related to the model’s performance. Besides, there is no direct way of determining the number of features to select from the resulting ranking of features.

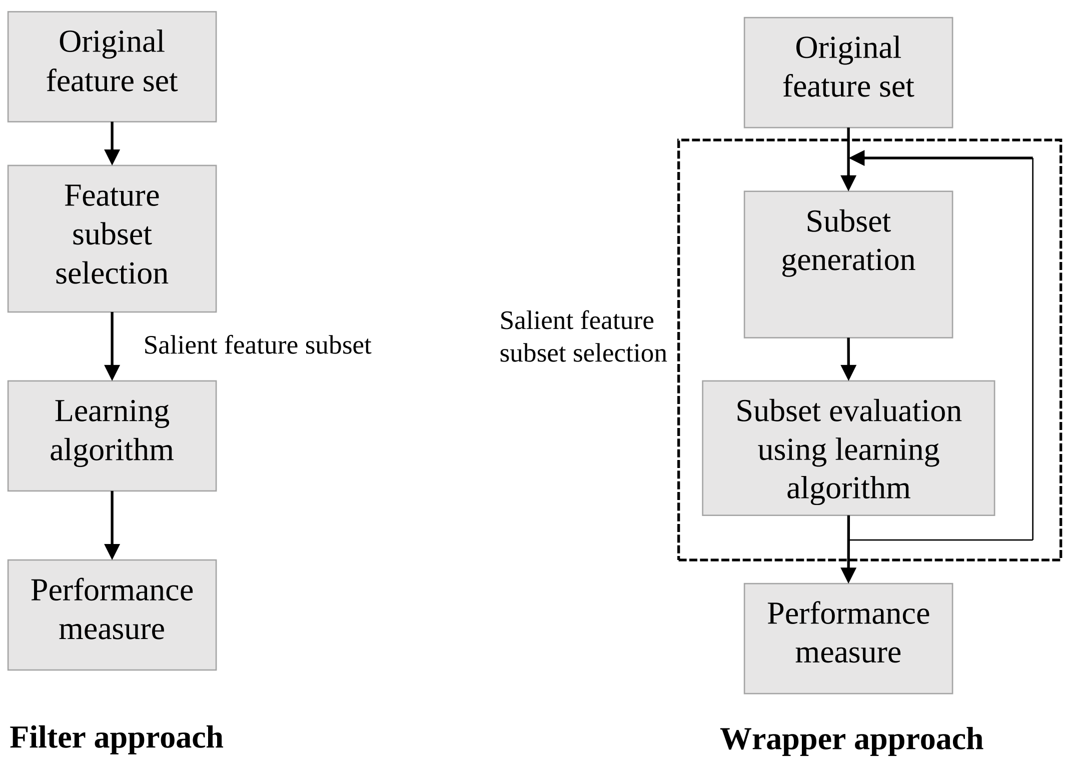


Figure 3.4: Flowchart of wrapper-based vs filter-based feature selection

Wrapper methods, on the other hand, consider feature dependencies and achieve, in most cases, a higher performance of the model as there is an interaction between the subset search algorithm and model selection. However, with wrappers, there is a higher risk of overfitting. More important is their computational cost as the number of models that need to be evaluated grows exponentially with the number of attributes. In this case, heuristic search methods are used.

Given the advantages they provide, we continue our analysis using wrappers. However, an exhaustive search in feature space is computationally intractable (with 21 indicators and using 10-fold cross-validation, 5×2^{22} models are built for each wrapping algorithm). A local optimum search algorithm, namely, Bi-directional Best-First with search termination after 10 non-improving nodes, is employed to find the best subset. A classifier is still to be specified to evaluate the subsets of features. For a more stable and robust feature selection, we use an ensemble feature selection instead. An ensemble of wrappers allows us to exploit the strengths of the individual selectors and overcome their weaknesses [44]. The outputs of feature selectors trained on the same data are combined, and the features with the highest scores are selected.

For choosing the classifiers to use for wrapping, we start with several methods known in the literature for being among the well-performing methods with different datasets. In their highly cited paper, Wu and colleagues 2008 [37] propose 10 algorithms that are widely used for different data mining tasks. Among these, six algorithms serve for classification tasks, namely, Naive Bayes, Support Vector Machine (SVM), C4.5, Classification and regression trees (CART), k-nearest neighbors (kNN), and Adaptive Boosting (AdaBoost). In [45], the authors evaluated 179 classifiers on 121 datasets. The highest results were obtained using the Random Forest algorithm (RF) and SVM. Other algorithms achieved remarkable performance, namely, C5.0 (a successor of C4.5), multi-layer perceptron (MLP), and AdaBoost.

With the algorithms mentioned above (except C5.0 as the advantages it provides over the classical C4.5 may not apply to our problem), we run a classification experiment on Weka's Experimenter interface to see whether some classifiers are better than other ones on our dataset and whether the difference is statistically significant or not. 1R, a simple algorithm that selects one attribute that best correlates with the class attribute and splits it up to get the best classification accuracy it can, is added to the previous set of classifiers to see if there is a single attribute that is highly discriminative. The experiment is conducted based on the idea that classifiers that perform well while using all features are good candidates to use for feature selection as they may be more suited to the characteristics of the dataset.

The models are evaluated using 10-fold cross-validation with 10 repetitions. The null hypothesis (one classifier's performance is the same as the other's) is tested with a 0.05 (two-tailed) significance Paired Corrected T-Test.

Table 3.3 shows the results of the experiment with SVM as its test base. The percentage accuracy presented in the table is the mean of the 10 repetitions. Multi-Layer Perceptron achieved higher accuracy than the SVM baseline, but the difference is not statistically significant. Naïve Bayes and Random Forest have a loss against the SVM baseline, but again one that is not statistically significant. Whilst all other classifiers performed worse. The top four algorithms will be later used for feature selection.

Table 3.3: Classification experiment results

Algorithm	Type	Proposed by	Name in WEKA	Percentage accuracy
Support Vector Machine (SVM) [1]	Support vector	[46]	SMO	92.23%
Multi-Layer Perceptron	Neural networks	[47]	MultilayerPerceptron	94.18%
Naive Bayes (NB)	Bayesian	[48]	NaiveBayes	89.83%
Random Forests	Ensemble	[49]	RandomForest	88.67%
Classification and Regression Trees (CART)	Decision tree	[50]	SimpleCart	85.14% *
C4.5	Decision tree	[51]	J48 [2]	82.17% *
k-Nearest Neighbors (kNN)	Instance based	[52]	IBk -K 1	68.99% *
			IBk -K 2	66.93% *
			IBk -K 3	69.88% *
			IBk -K 4	65.91% *
1R	Rule based	[53]	OneR	67.46% *
AdaBoost	Ensemble	[54]	AdaBoostM1	51.05% *

[1] The classifier is the reference in the experiment
[2] A Java implementation of C4.8 algorithm, a minor extension to C4.5
* Statistically significant loss against the baseline algorithm

In the next paragraphs, we provide a summary of how these algorithms function:

- **Naïve Bayes:**

Naïve Bayes is a simple classifier that uses Bayes' rule of conditional probability. The classifier supposes the conditional independence of explanatory variables. The presence or absence of an attribute is not related to the presence or absence of all other attributes given the class [48]. The class with the highest probability is assigned to the feature vector. Indeed, features are rarely independent given the class. Still, Naïve Bayes has shown agreeable performance in cases where the features are highly correlated [55]. Due to its simplicity, Naïve Bayes is particularly useful in problems with high dimensionality.

The probability that an instance x belongs to a class c (the posterior probability) can be calculated as follows:

$$P\left(C=c \mid X=x\right)=\frac{P\left(C=c\right)\prod_{i} P(X_i=x_i \mid C=c)}{P(X=x)} \quad \textbf{(3.1)}$$

$$P(X=x)=\sum_{j} P(C_j)P(X=x \mid C_j) \quad \textbf{(3.2)}$$

$P(C=c)$: called the prior probability, is found by counting how many times the class c occurs in the training dataset.

Equation 3.1 is valid only if the attributes X_i are qualitative (nominal). Quantitative attributes can be handled by modelling them with a continuous probability distribution or by using discretization [56].

- **Support Vector Machine (SVM):**

SVM classifiers try to find the optimal separation of classes using one or multiple hyperplanes. In order to make the separation easier, a function (known as a kernel) maps the training instances into a high-dimensional feature space non-linearly. Different types of kernel functions can be used for separation, such as Gaussian, polynomial, and sigmoid. A hyperplane is then created within this new feature space in a way that maximizes the distance (i.e., “the margin”) between the hyperplane and the nearest instances from the opposing classes (known as the support vectors) [46,57] (Figure 3.5).

The SVM was developed initially for binary classification problems. In order to apply the SVM for situations where there are multiple classes, the multi-class problem is decomposed into several two-class problems [58].

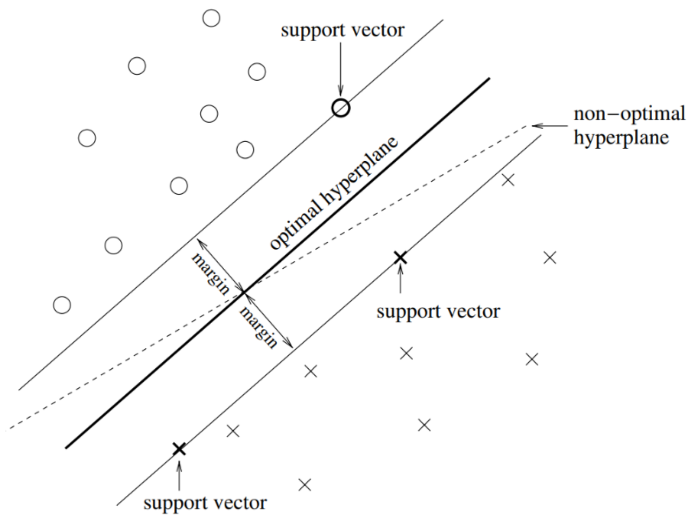


Figure 3.5: SVM optimal hyperplane [59]

SVMs are deemed to be relatively less prone to the class imbalance problem than other classification algorithms, as the boundaries between classes are determined merely in terms of the support vectors, regardless of the class sizes [60].

- **Random Forests (RF):**

Random Forests is an ensemble classification method that constructs a collection of decision trees. "Decision trees are trees that classify instances by sorting them based on feature values. Each node in a decision tree represents a feature in an instance to be classified, and each branch represents a value that the node can assume. Instances are classified starting at the root node and sorted based on their feature values". "The feature that best divides the training data would be the root node of the tree". For random forest, at each node of a classification tree, only a limited number of randomly chosen variables are available for the binary partitioning of the tree. The trees are fully grown and the predicted class of an observation is determined by the majority vote from the ensemble for that observation [49,61]. Figure 3.6 is a simple illustration of a random forest classifier [62].

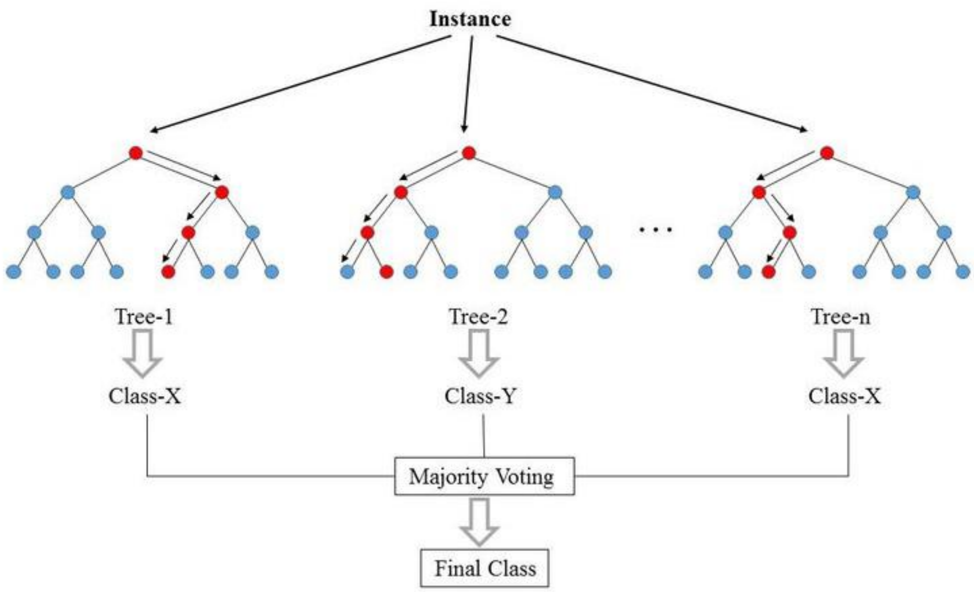


Figure 3.6: Random Forest algorithm

- **Multilayer Perceptron (MLP):**

The multilayer perceptron is the most popular artificial neural networks (ANN) classifier. An ANN is an algorithm that simulates how the biological nervous system operates, by having multiple interrelated processing elements (neurons), functioning in unity to solve a particular problem. In a single neuron, a series of features and associated weights pass through a sigmoid function. A neural network is a group of neurons connected in layers [63,64]. “An MLP is composed of several layers of neurons: an input layer, possibly one or several hidden layers and an output layer. Each neuron’s input is connected with the output of the previous layer’s neurons whereas the neurons of the output layer determine the class of the input feature vector” [59]. Figure 3.7 depicts a simple schematic of a multilayer perceptron neural network with two hidden layers for predicting a categorical variable for the magnitude of an earthquake [65].

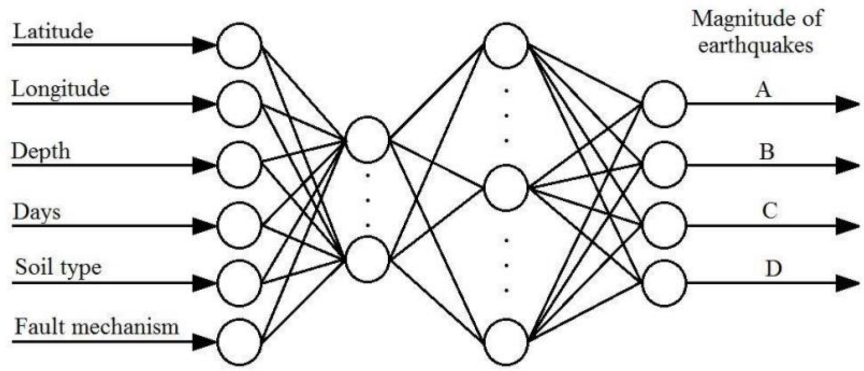


Figure 3.7: Multilayer perceptron for earthquake magnitude classification

We use the Weka Explorer to perform feature selection with the four wrapping algorithms using the "WrapperSubsetEval" technique and 10-fold cross-validation. The search method employed is the Bi-directional Best-first with search termination after 10 non-improving nodes.

Once feature selection is made, each fold and selector's outputs are combined to produce a final ranking of features. The ranking derives from the total number of times a feature takes part in an optimal subset for each fold and selector. Thus, with 10-folds and four wrapping algorithms, a feature selected in all optimal subsets will have a total score of 40 (Figure 3.8).

Thresholds of 10% and 25% of features are practical thresholds in the literature to determine the cardinality of the final set of features. Wang, Khoshgoftaar, and Napolitano 2010 [66] propose a threshold of $\log2(n)$, where n is the number of features. A fundamental problem with these fixed thresholds is that they ignore the fact that the number of features to retain depends on the characteristics of the dataset subject to analysis. To take this into account, we go for thresholding constructed on data complexity measures. The complexity measure we have chosen is the maximum Fisher's discriminant ratio (F1). It measures the overlap between the values of the features in different classes:

$$F1 = \frac{1}{1 + \max_{i=1}^{n} f_i} \quad \textbf{(3.3)}$$

$$f_i = \frac{\sum_{i=1, j=1, i \neq j}^{c} p_i p_j (\mu_i \mu_j)^2}{\sum_{i=1}^{c} p_i \sigma_i^2} \quad \textbf{(3.4)}$$

where f_i is a discriminant ratio of feature i. $F1$ is basically the maximum of f_i, but in this paper, we use the inverse with values in the interval $(0,1]$ such that lower values represent an easier problem [67].

μ_i, σ_i^2, and p_i are the mean, variance, and proportion of the ith class, respectively.

We want to minimize the fitness criterion $e[v]$:

$$e[v] = \alpha \times F1 + (1-\alpha) \times FeaturePercentage \tag{3.5}$$

where: v : is any possible value for the threshold.

$FeaturePercentage$: the percentage of features retained, which should be minimized.

α : a parameter in $[0,1]$ which measures the relative relevance of the complexity measure and the feature percentage ($\alpha = 0.75$ is chosen for this work).

Using the fitness criterion, we can find the threshold using Algorithm 3.2, which we adapted from [68] to fit our method of combining feature subsets.

Features above the threshold are retained. Then, weights are assigned to features according to the proportion of their frequencies in the total number of selected features in all optimal subsets.

The final output of feature selection is a weighted sum of selected features, which afterward is combined with the DALYs in a geometric mean. The geometric mean is mainly chosen because we combine measures of different nature: health determinants, and a metric of health status. The resulted score serves as a basis for the ranking of countries:

Country score = Geometric mean (weighted sum of selected indicators, normalized DALYs).

Algorithm 3.2: Pseudocode to determine the cardinality of the final subset

Inputs:

$f = (1, \ldots, i, \ldots, n)$ ▹ feature vector

n ▹ number of weak selectors

F_i ▹ total frequency of selection of feature i in all folds and selectors combined

Result: S ▹ final subset of features

for $j = 1$ to n do

  if $n - \frac{F_i}{10} > j$ then $v_i \leftarrow v_i + 1$

  end if

▹ increment one vote for each feature not appearing in every 10 of the total number of optimal subsets (for a 10-fold cross-validation and n selectors, the total number of optimal subsets is $10n$)

end for

for $v = 0$ to n do

  $Fth \leftarrow$ { subset of features with number of votes $\leq v$ }

  $F1 \leftarrow$ F1 value of computed on Fth

  $Feature\ Percentage \leftarrow$ percentage of features retained

  $e[v] = \alpha \times F1 + (1 - \alpha) \times Feature\ Percentage$

end for

$Th \leftarrow min(e)$ ▹ Th is the value which minimizes the error e

$S \leftarrow$ subset of features after removing all features with a number of votes $> Th$

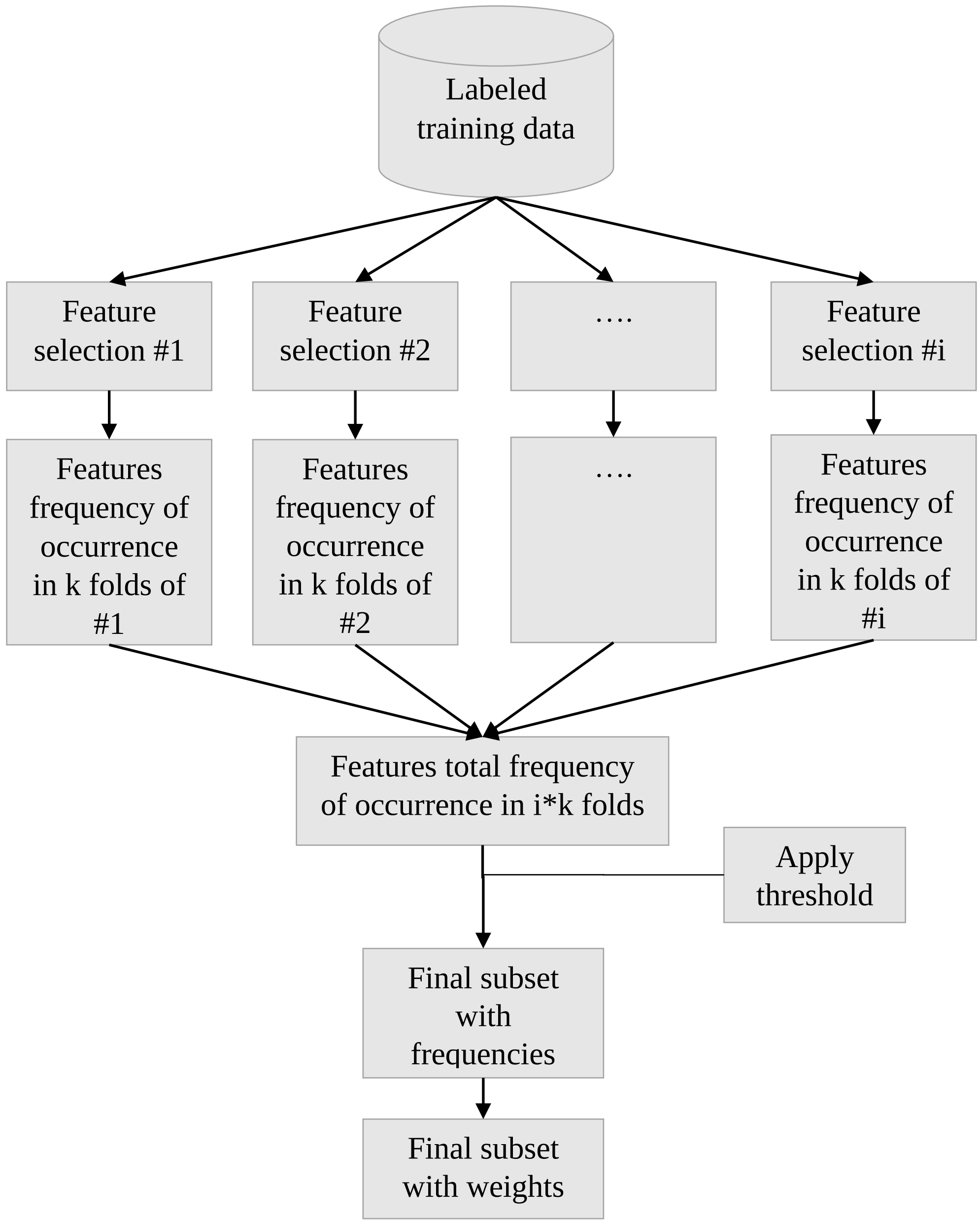


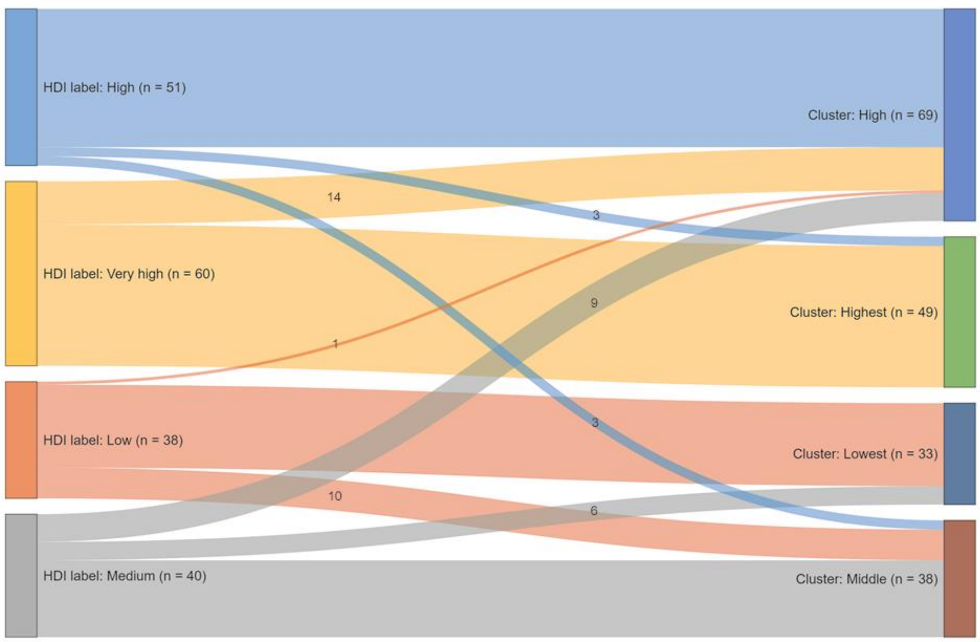
Figure 3.8: Ensemble feature selection approach

Chapter 4

Results

4.1 Clusters of countries

For three-quarters of countries, the groups of membership for the clustering are similar to their HDI groups, which may be an indication of reliable clustering (Figure 4.1).



Note: the clusters were named based on characteristics of countries dominating each cluster.

Figure 4.1: Sankey diagram for clustering – HDI correspondance

Table 4.1 shows the mean values of each feature by the cluster. Cluster 3 has the most preferred values for all measures except for total debt service. While Cluster 2 has the least favorable values for all features except for the incidence of HIV and tuberculosis. In the table, darker shades of orange represent the least preferred values, while the darker shades of blue represent the most preferred ones. The multivariate R-squared statistic shows the proportion of variance in the cluster assignment that is explained by each variable. Five variables explain more than 70% of variation with three variables that have values of more than 80%.

Table 4.1: Resulting clusters and centers

	Cluster 2	Cluster 4	Cluster 1	Cluster 3	R^2	p
	n=33 17%	n=38 20%	n=69 37%	n=49 26%		
Births attended by skilled health staff	0.54	0.73	0.97	0.99	0.61	< .001
Current health expenditure per capita, PPP	0.01	0.03	0.1	0.37	0.65	< .001
Domestic general government health expenditure per capita	0	0.02	0.07	0.34	0.64	< .001
GINI index	0.47	0.44	0.37	0.17	0.31	< .001
GNI per capita, PPP	0.02	0.04	0.12	0.37	0.65	< .001
Hospital beds per 1,000 people	0.08	0.11	0.24	0.37	0.27	< .001
Immunization DPT	0.7	0.83	0.93	0.93	0.26	< .001
Incidence of HIV	0.1	0.13	0.02	0.01	0.13	0.001
Incidence of malaria	0.41	0.06	0	0	0.63	< .001
Incidence of tuberculosis	0.31	0.35	0.06	0.03	0.47	< .001
Income share held by lowest 40%	0.51	0.52	0.59	0.8	0.28	< .001
Nurses and midwives per 1,000 people	0.03	0.09	0.2	0.5	0.65	< .001
Out-of-pocket expenditure	0.51	0.43	0.47	0.25	0.16	< .001
People using at least basic drinking water services	0.3	0.71	0.93	0.98	0.84	< .001
People using at least basic sanitation services	0.21	0.54	0.91	0.98	0.86	< .001
Physicians per 1,000 people	0.02	0.06	0.26	0.45	0.66	< .001
Poverty gap at $1.90 a day	0.48	0.08	0.01	0.01	0.74	< .001
Poverty headcount ratio at $1.90 a day	0.65	0.16	0.02	0	0.85	< .001
Tax revenue (% of GDP)	0.34	0.44	0.47	0.49	0.08	0.001
Total debt service (% of GNI)	0.08	0.1	0.2	0.68	0.49	< .001
Mean years of schooling	0.23	0.38	0.64	0.81	0.73	< .001

The p-values demonstrate that all the variables are significant in explaining the cluster assignment.

Now each country has a class label, which is the cluster to which it was assigned. Feature selection can allow then to define a subset of features that delivers much the same grouping.

4.2 Selected indicators

The process of feature selection led to selecting an optimal subset of features for each of the 10 folds for each of the four wrapping methods. Hence, a feature selected in every fold will have a total frequency of 40 in the total number of optimal subsets. The results reveal that four indicators have a frequency greater than or equal 30, nine features with frequencies in the interval [20,30), five features in the interval [10,20), and the remaining three features with frequencies less than 10. The frequency of each feature's selection in optimal subsets for each selection method with their total frequencies are provided in Appendix 1.

The application of a selection threshold suggests to retain the top four features; weights are assigned to these features according to the proportion of their frequencies in the total number of selected features in all folds and methods (see Appendix 1). The selected indicators and associated weights are:

0.25 × Domestic general government health expenditure per capita, PPP

0.26 × People using at least basic drinking water services (% of population)

0.26 × People using at least basic sanitation services (% of population)

0.23 × Mean years of schooling (years)

An ensemble filter feature selection proposes the same four features. However, the ranks of other features are considerably different. Figures 4.2 to 4.5 display the values of the four selected indicators across countries for the year 2016.

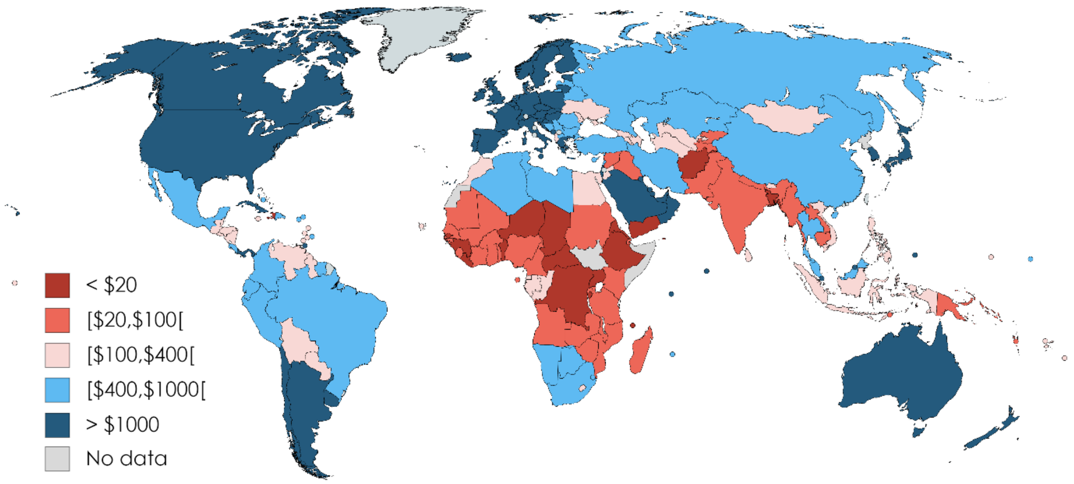


Figure 4.2: Domestic general government health expenditure per capita, PPP (current international $), 2016

Data source: World Bank [32].

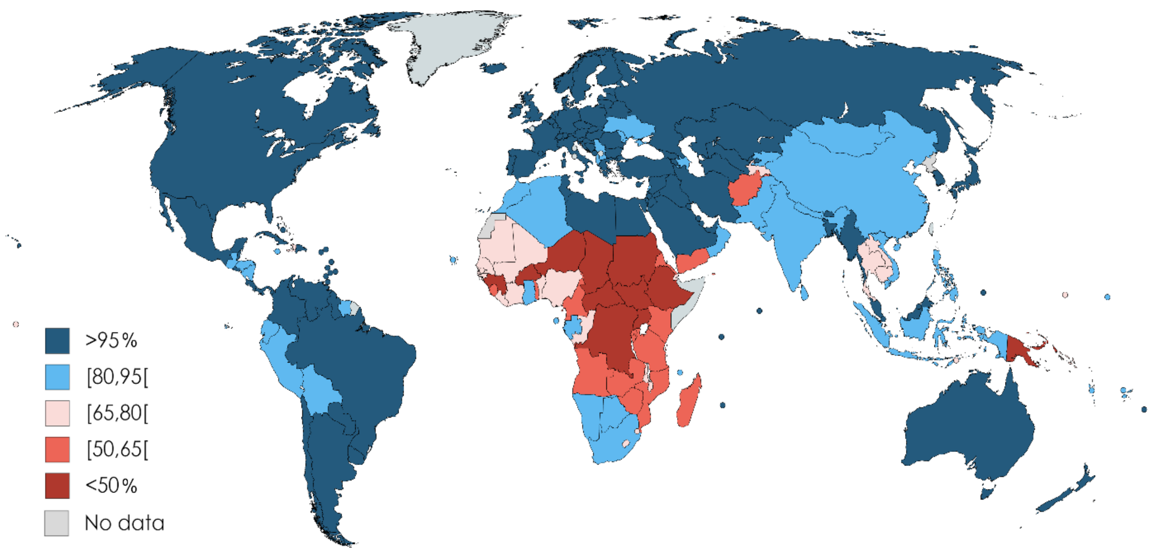


Figure 4.3: People using at least basic drinking water services (% of people), 2016

Data source: World Bank [32].

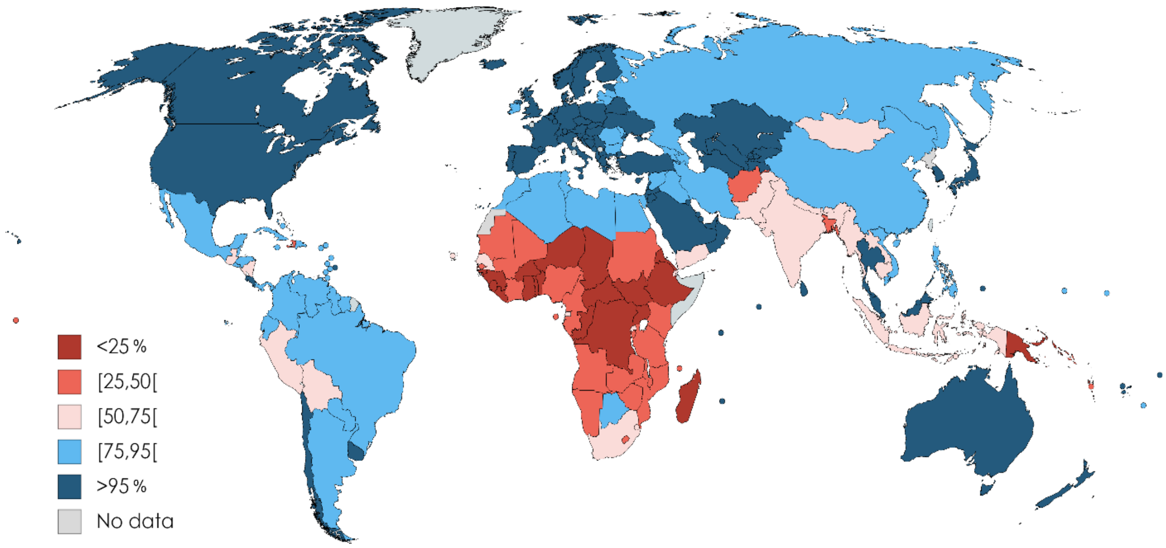


Figure 4.4: People using at least basic sanitation services (% of people), 2016

Data source: World Bank [32].

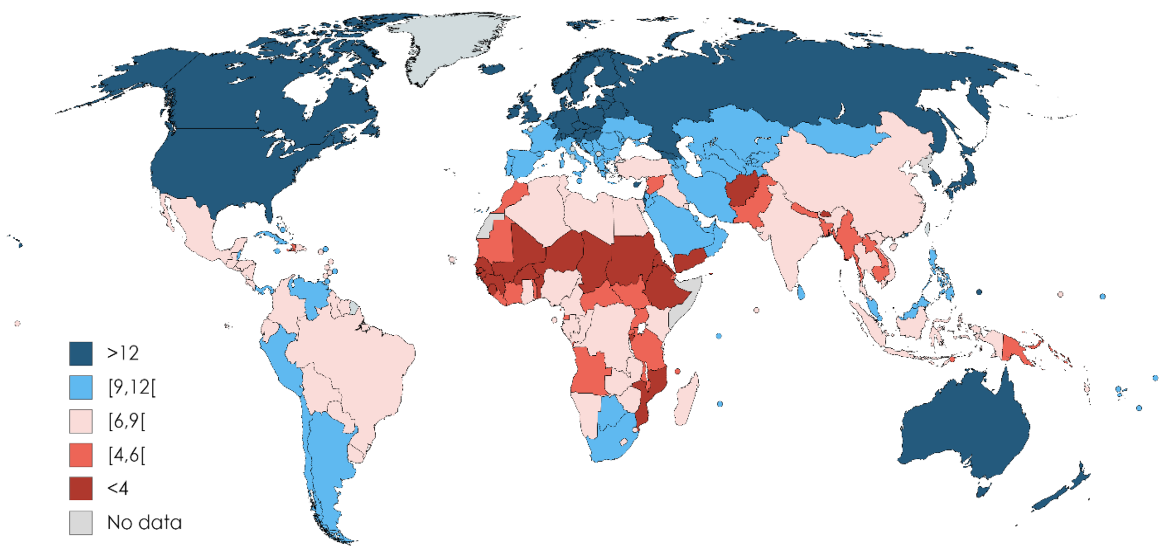


Figure 4.5: Mean years of schooling, 2016

Data source: UNDP [33].

4.3 Countries scores

We calculate a country score as follows:

Country score = Geometric mean (weighted sum of selected indicators, 1 – normalized DALYs)

The complement of DALYs is used here instead of the DALYs for coherence. Higher values for the four selected indicators are preferred, and higher values for the complement of DALYs are preferred as well.

We then rank the countries according to their scores. Interestingly, the weights for the four selected indicators are very close, a thing that encouraged us to examine the possibility of using equal weights as it brings more simplicity to the framework, which is a priority for the decision-makers.

Table 4.2: Countries rank change when moving from original weights (rank1) to equal weights (rank2)

	Rank change	
Rank 2 lowest 20%	Min	-1
	Median	0
	Avg abs	0.27
	Max	2
Rank 2 second 20%	Min	-2
	Median	0
	Avg abs	0.22
	Max	1
Rank 2 third 20%	Min	-4
	Median	0
	Avg abs	0.89
	Max	3
Rank 2 fourth 20%	Min	-3
	Median	0
	Avg abs	0.89
	Max	3
Rank 2 highest 20%	Min	-2
	Median	0
	Avg abs	0.32
	Max	2

Table 4.2 shows that there are no remarkable changes in ranks when switching to equal weights. Therefore, we decided to use the average of selected indicators. A country's score is eventually calculated this way:

Country score = Geometric mean (average of selected indicators, 1 - normalized DALYs)

The values of indicators, DALYs, and final scores for countries are available in Appendix 2. A comparison in ranks between our framework and GNIpc and HDI are also included.

Figures 4.6 and 4.7 illustrate the correspondence between the countries' ranks resulting from our framework and the ranks that derive from using GNI and HDI. We find a linear relationship in both cases. Also, the points are less scattered for the HDI, which marks the proceeding from an income-based to a development-based evaluation of countries.

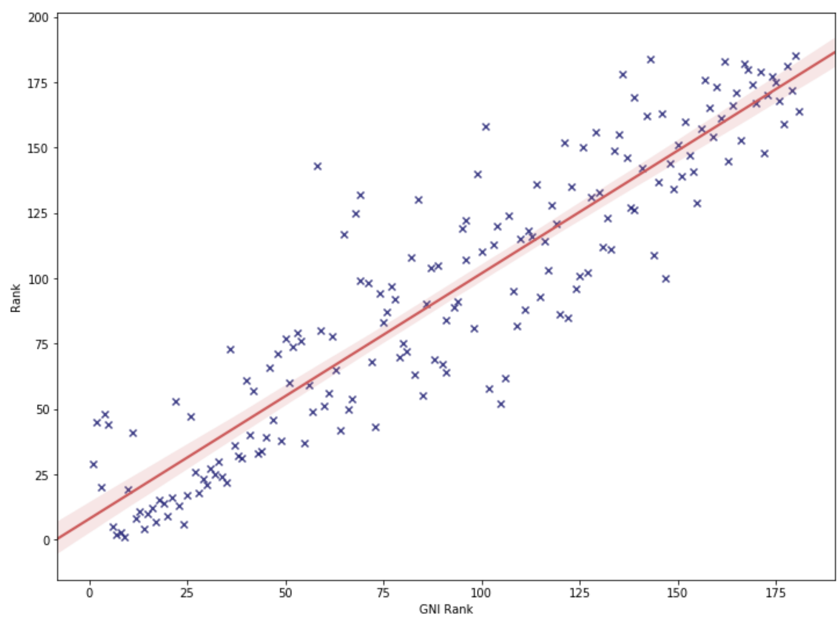


Figure 4.6: Scatter plot describing the relationship between GNI countries' rank and ranks resulting from our framework

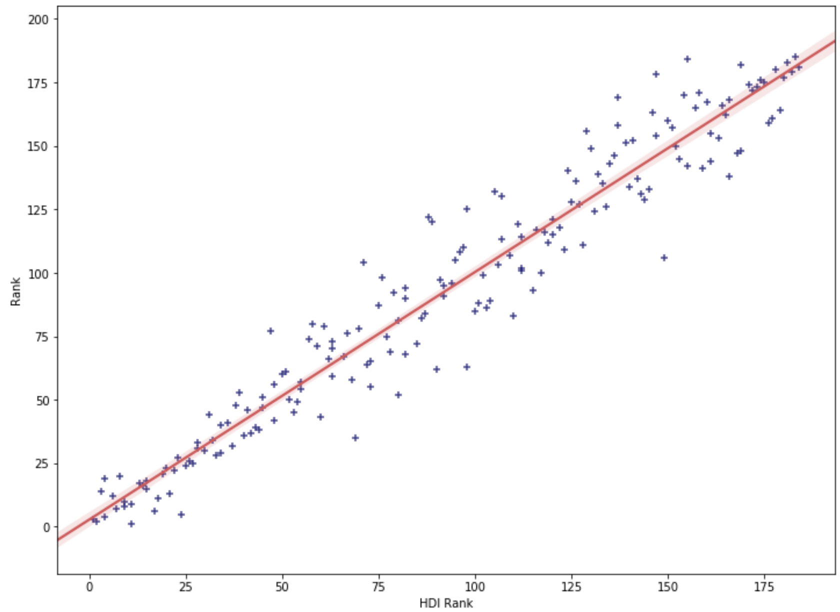


Figure 4.7: Scatter plot describing the relationship between HDI countries' rank and ranks resulting from our framework

4.4 Framework Evaluation

To evaluate our framework, we compare it to the GNIpc and the frameworks proposed by the Equitable Access Initiative teams. We rely on the correlation with three fundamental measures for our comparison: GNIpc, age-standardized DALYs, and Gini index. As a measure of correlation, we choose the Spearman's rank correlation coefficient. A correlation of +1 or −1 indicates a perfect monotonic relationship, while values closer to 0 show a weaker monotonic relationship. We prefer a high correlation with the DALYs, which quantify the disease burden, a high correlation with the Gini index, meaning that countries with high inequalities and preferred. Moreover, we prefer a correlation with GNIpc that is high enough. A low correlation with the GNIpc means many countries have a dramatic change in rank, resulting in some countries losing their eligibility for aid completely while moving to our framework and witnessing a severe shock in their health systems. Still, a marked shift in ranks is needed.

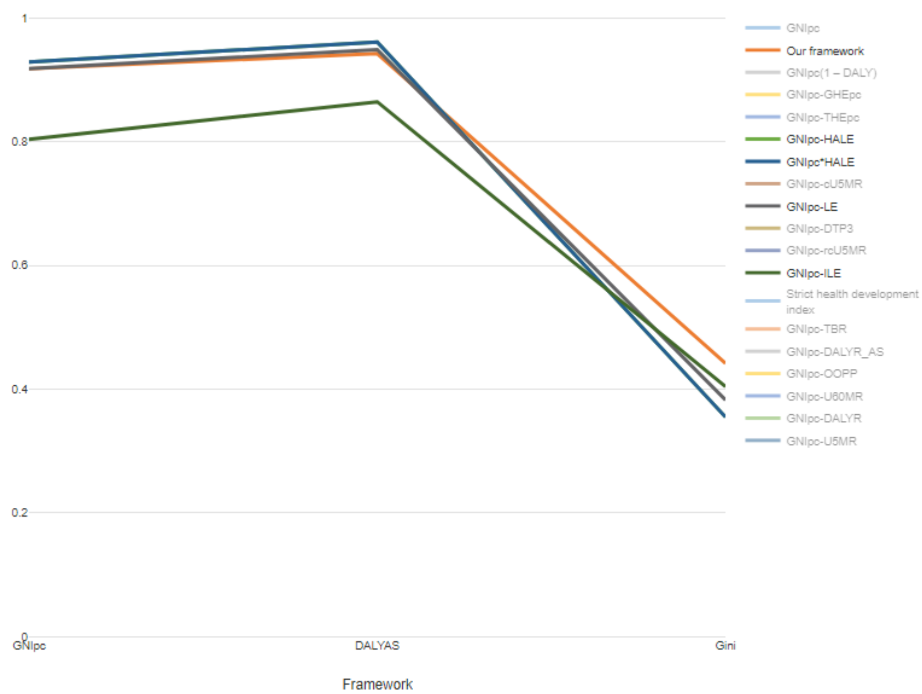


Figure 4.8: Spearman correlation of frameworks with fundamental indicators

Figure 4.8 depicts the comparison of the different frameworks with the non-dominated ones only visible. Our framework correlates highly with the DALYs and is the most highly associated with the Gini index. Its correlation with GNIpc seems too high to serve as an alternative for it. Still, the average and median of absolute change in rank are 16.5 and 13, respectively (note: Pearson's correlation coefficient = 0.67).

The SDGs emphasize the importance of targeting poor people wherever they are [69]. With our framework, populations that their rank improves while moving from GNIpc to our framework are almost four times the ones that their rank deteriorates, with 35 countries positively affected and 14 negatively affected (Figure 4.9).

We repeat the same comparison; this time, we add the non-dominated frameworks in figure 4.8 to compare with GNIpc. Again, with our framework, more countries and people in extreme poverty are positively affected, when fewer countries and people in extreme poverty have their ranks dropped (Table 4.3).

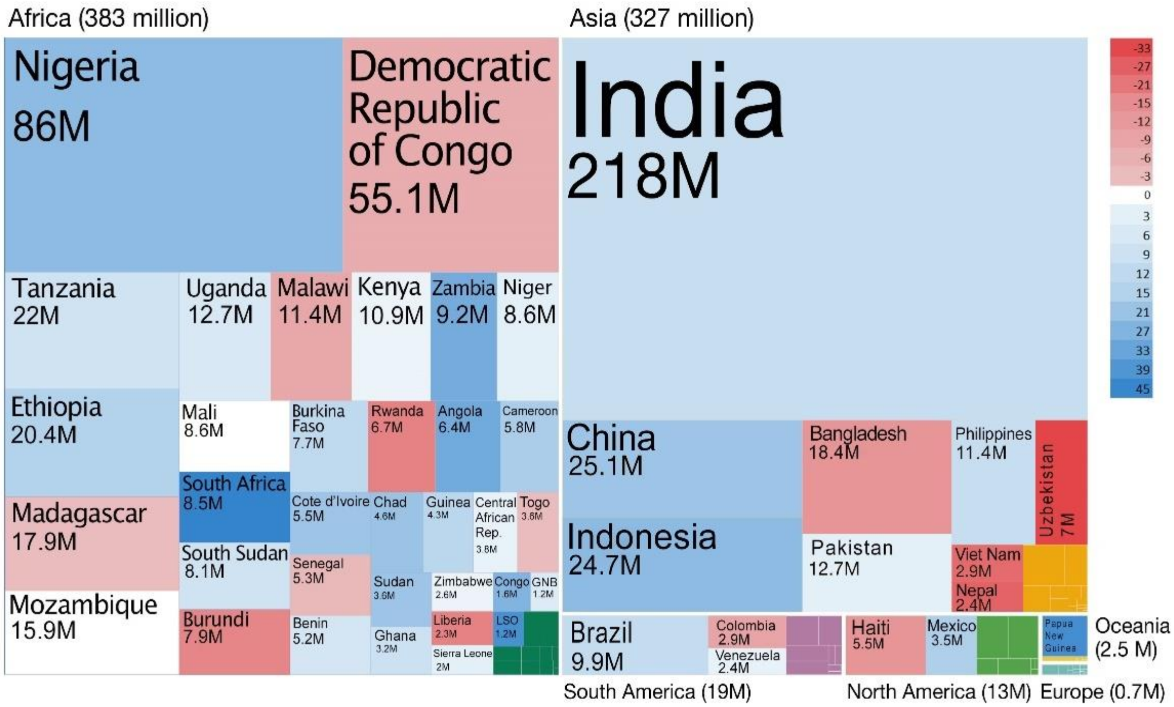


Figure 4.9: Treemap of rank change while moving from GNIpc to our framework for populations in extreme poverty

Sources: Poverty data retrieved from World Bank PovcalNet [70].

Table 4.3: Changes for countries with high populations of people in extreme poverty with performing frameworks when moving from GNIpc

		Our framework	GNI-HALE	GNI-LE	GNI-ILE
Negatively affected	Total population (millions)	149.1	273.2	286.8	300.8
	Average rank change	-14.07	-16.63	-15.13	-14.28
	Number of countries	14	27	24	29
Positively affected	Total population (millions)	569.5	456.2	456.3	438
	Average rank change	15.11	14.65	16.19	17.76
	Number of countries	35	23	27	21

4.5 The framework at a subnational level

We attempt to apply the framework at a subnational level to learn if it can help target more impoverished, at high-risk people. Finding data for all indicators at a subnational level is quite challenging. The DALYs at the subnational level are available only for several middle-income and high-income countries. We present here the examples of Brazil and Mexico (middle-income countries), and the United States (a high-income country). The United States is not a recipient of development assistance. In fact, it is the largest donor country of foreign aid [71]. Our main purpose of presenting this example here is to show that multicriteria frameworks can help in developing public health policies at the national level.

4.5.1 Brazil

Data on DALYs for Brazil are accessible from [31], government health expenditure per capita are available in [72], mean years of schooling and GNIpc in [34], and data about access to water and sanitation in [73]. All data belong to the year 2017. As a measure of income inequality, data for the Gini index are available for the year 2012 (the most recent year available) in [74].

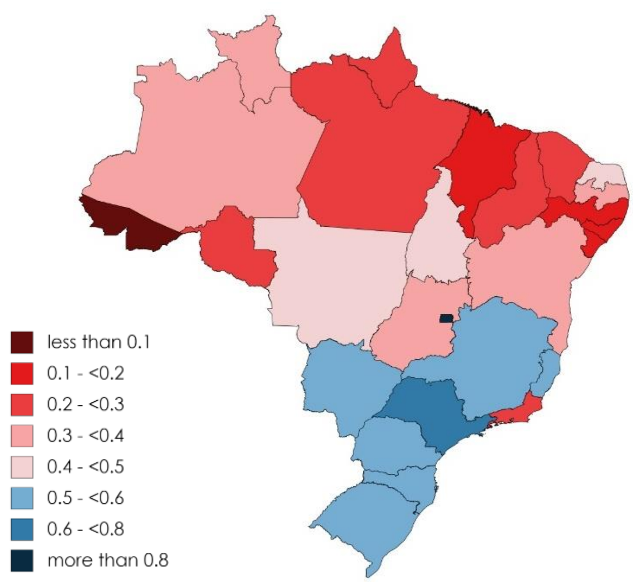


Figure 4.10: Brazilian states scores with our framework

Table 4.4: Spearman correlation of frameworks with key indicators for Brazilian states

		Per capita income	Our framework
DALYs	All states	0.48	0.79
	Income lowest 25% states	0.64	0.61
Gini	All states	0.47	0.44
	Income lowest 25% states	0.39	0.59

The scores for the 27 Brazilian states with our framework are displayed in figure 4.10. A North-South divide can be clearly seen, with the most disadvantaged states in the North. A comparison of the framework with the per capita income shows that our framework is more highly correlated with the DALYs when considering all states and outperforms the per capita income in targeting states with the highest inequalities within the lower 25% states in terms of average income. However, the per capita income has a slightly higher correlation with the Gini index for all states and with the DALYs for the lower 25% states with regard to average income (Table 4.4).

4.5.2 Mexico

Data on DALYs for Mexico are accessible from [31], government health expenditure per capita are available in [75], mean years of schooling and GNIpc in [34], data about access to water and sanitation in [76], and data for the Gini index are available in [77]. Data for water and sanitation are for the year 2015. All other data belong to the year 2016.

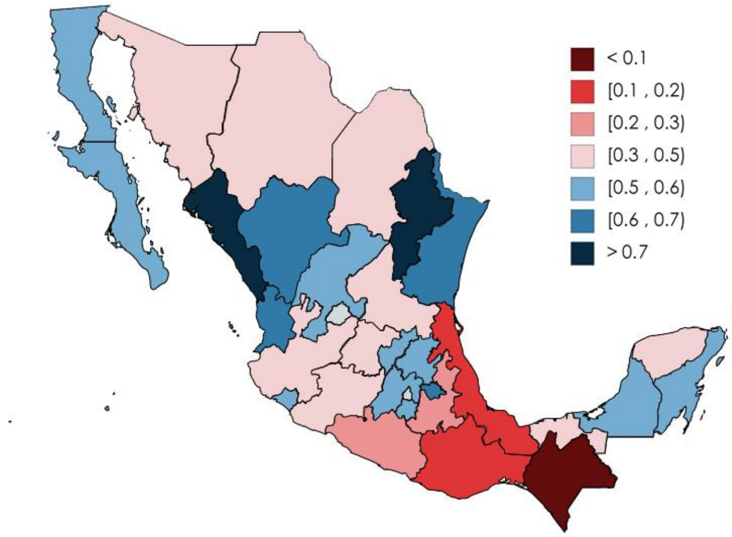


Figure 4.11: Mexican states scores with our framework

Table 4.5: Spearman correlation of frameworks with key indicators for Mexican states

		Per capita income	Our framework
DALYs	All states	-0.09	0.80
	Income lowest 25% states	0.37	0.83
Gini	All states	-0.17	0.17
	Income lowest 25% states	0.64	0.90

The scores for the 32 Mexican states with our framework are given in figure 4.11. The most disadvantaged states are clustered in the southern part of the country and near the United States' borders. Comparing the framework with the per capita income shows that our framework correlates highly with the DALYs, while per capita income has a low or negative correlation. The correlation of the framework with the Gini index is low but still a positive one, which is not the case for income per capita. When considering the lower 25% states in terms of average income, the framework has a very high correlation with the Gini index while income per capita has a moderate one (Table 4.5).

4.5.3 The United States

Data for the DALYs for the United States are accessible from [31]. Government health expenditure data on a state level are not available. Instead, we used Medicaid expenditure for each state [78] divided by the population in each state [79] to obtain Medicaid expenditure per capita. Mean years of schooling and GNIpc are found in [34]. Data about the coverage of basic water and sanitation services are not available, we used the percentage of houses lacking complete plumbing facilities as an alternative indicator [79].

The score for each state is then given as follows: Score = geometric mean (1 – normalized DALYs, average of normalized (mean years of schooling, Medicaid expenditure per capita, percentage of houses having plumbing facilities)).

As a measure of income inequality, data for the Gini index are available in [80]. For all indicators, data represent the year 2017.

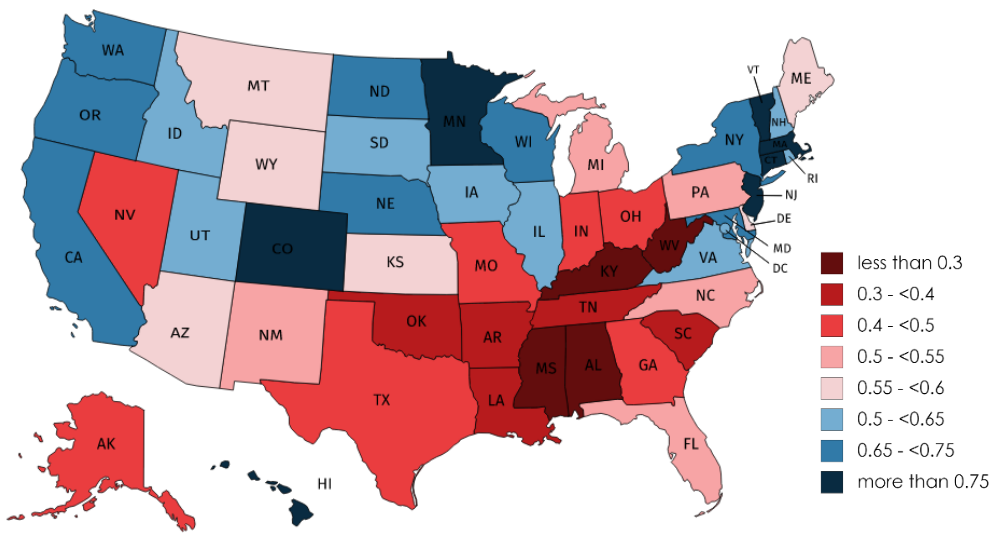


Figure 4.12: Scores of states of the United States with our framework

Table 4.6: Spearman correlation of frameworks with key indicators for states of the United States

		Per capita income	Our framework
DALYs	All states	0.54	0.91
	Income lowest 25% states	0.04	0.93
Gini	All states	0.10	0.27
	Income lowest 25% states	-0.20	0.66

The scores for the 51 states and territories of the United States with our framework are displayed in figure 4.12. The most disadvantaged states according to our analysis are concentrated in the Southeast region.

Table 4.6 shows that our framework wins the per capita income in directing attention towards states with a higher burden of disease and higher inequalities in income. For the lower 25% states in terms of average income, the per capita income does not correlate with the DALYs and surprisingly has a negative correlation with the Gini index meaning that it gives less priority to the states that have higher income inequalities.

Chapter 5

Conclusions and Future Prospects

5.1 Conclusions

Development assistance for health is an essential contributor to improving health outcomes in developing countries and supporting them to achieve the Sustainable Development Goals (SDGs). However, increasing funds is never enough if these funds are not directed toward regions of remarkable gaps. The focus of development assistance for health should indeed be on regions with high disease burden and low capacity of response. In this project, we tried to build on previous works in this topic to try to come up with a framework that is reasonably comprehensive of different dimensions of the problem, that is more based on evidence from data than on dispersed propositions of experts, and that avoids pitfalls and limitations of previous works: a framework that guarantees at its end more reliable decision making.

The indicators composing our framework are simple and available for different countries, things that could encourage decision-makers to rely on them. Additionally, while inequality measures lack completeness (which makes them not favorite candidates for feature selection), income share held by the lowest 40% of the population (36.5% of missing data) came in rank right after the four selected indicators. This outcome aligns with the 2019 Human Development Report's theme of moving beyond averages and focusing on inequalities [81]. Nevertheless, while we presented a lack of inequality measures as a critique for the Equitable Access Initiative, our approach still includes these measures implicitly as it integrated them for finding the clustering of countries that guided the selection of indicators.

Our framework outperformed the GNIpc and most other frameworks in prioritizing countries with a higher burden of disease and countries with large populations in extreme poverty. We found supportive results as well while applying the framework at a subnational level.

Our work has some limitations related to (i) relevant problem dimensions: while we started with a broad set of indicators, the studied literature may have ignored other indicators that could be relevant (ii) missing data: data availability for some indicators may affect the quality of our initial clustering. However, for the indicators composing the final formula, data missingness was not an issue (iii) computational complexity in feature selection: we used a search for local optimum to find the best subset for each fold and feature selector. An exhaustive search requires building 5×2^{24} models.

Finally, the framework we proposed may not necessarily serve as an alternative to GNIpc. Our main contribution is to add to the debate about what should direct decisions about aid eligibility and allocation.

5.2 Societal Impact and Contribution to Global Sustainability

Health is represented in the Sustainable Development Goals (SDGs) by Goal 3: Ensure healthy lives and promote well-being for all at all ages. With ten years left to finish the 2030 SDGs agenda, additional efforts are needed from the global community to reach the defined targets. Many countries may miss several health targets, but more financial resources, cooperation, and better policies could make reaching the targets possible. One instrument that could help accelerate the progress is development assistance for health. An increase in development assistance and amelioration of its management will support poor countries in providing health services and sustaining their health reform efforts. Our thesis comes in this context with a new perspective for deciding on eligibility and allocation of development assistance for health. Our data show that the framework we developed gives more priority to countries with larger burden of disease and less capacity to address health challenges. It gives also more consideration to populations in extreme poverty whether they are in poorer or richer countries. The framework proved also its usefulness in guiding national health policies and reducing geographical inequalities. Finally, our methodology can be examined for applicability by the global community to guide vertical health programs and also to shed light on other developmental targets by defining the relevant indicators to start with.

5.3 Future Prospects

We are currently investigating the causes behind the remarkable change in rank for some countries while moving from GNIpc to our framework, and we are also trying to find out if that change is justified.

To further our research, we plan to study the potential positive or negative effects of applying our framework on the health systems of countries with remarkable rank change. Our methodology could also be enhanced by improving the quality of the clustering and feature selection (algorithm choice, parametrization). While a sensitivity analysis could help checking the robustness of our results.

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Appendix 1: Feature Selection Results

Attribute *	Naïve Bayes	SVM	MLP	RF	Total freqs.	Weight	Top 4
1	0	4	1	2	7	0.016	
2	0	5	2	0	7	0.016	
3	8	8	7	10	33	0.076	0.25
4	4	7	2	6	19	0.044	
5	5	10	4	1	20	0.046	
6	2	8	3	4	17	0.039	
7	3	5	8	6	22	0.051	
8	1	1	2	4	8	0.019	
9	1	6	8	7	22	0.051	
10	1	9	6	6	22	0.051	
11	4	6	9	5	24	0.056	
12	4	5	7	0	16	0.037	
13	2	8	4	6	20	0.046	
14	6	10	10	9	35	0.081	0.26
15	10	8	10	7	35	0.081	0.26
16	6	6	3	4	19	0.044	
17	4	4	2	3	13	0.030	
18	9	0	8	5	22	0.051	
19	7	7	3	4	21	0.049	
20	4	6	4	6	20	0.046	
21	4	10	8	8	30	0.069	0.23
					432		

* The order is the same as Table 3.3.2.1

Appendix 2: Indicators Values and Ranks Comparison

Countries	Births attended by skilled health staff (% of total)	Current health expenditure per capita, PPP (current international $)	Domestic general government health expenditure per capita, PPP (current international $)	GINI index (World Bank estimate)	GNI per capita, PPP (current international $)	Hospital beds (per 1,000 people)
Afghanistan	53.09	162.78	8.35		1910	0.54
Albania	99.69	759.67	314.17	28.00	12060	2.89
Algeria	96.60	998.15	675.62		14900	1.90
Andorra		4978.71	2446.03			
Angola	49.60	185.82	82.02		6410	
Antigua and Barbuda	100.00	976.39	591.24		22580	4.60
Argentina	100.00	1531.04	1139.52	42.00	19690	5.28
Armenia	99.80	876.86	144.27	32.50	9000	4.25
Australia	99.74	4529.89	3094.25	35.81	46210	3.79
Austria	98.40	5295.18	3839.56	30.95	51600	7.60
Azerbaijan	99.80	1193.06	238.18		16280	1.90
Bahamas	98.90	1435.57	715.78		30050	2.69
Bahrain	100.00	1866.30	1145.24		44120	1.51
Bangladesh	49.80	90.60	16.27	32.40	3910	0.77
Barbados	98.73	1322.99	607.08		17150	5.28
Belarus	99.80	1151.41	707.50	25.30	17270	11.20
Belgium		4667.88	3925.96	27.68	47270	6.08
Belize	96.80	541.43	359.12		7870	1.09
Benin	78.24	83.48	17.14	48.90	2160	
Bhutan	89.00	293.11	216.76	37.68	8850	1.30
Bolivia	89.80	496.31	326.07	44.60	7020	1.10
Bosnia and Herzegovina	99.90	1123.43	795.24		12860	3.50
Botswana	100.00	931.30	520.90	52.10	16650	1.80
Brazil	99.24	1777.47	590.55	53.70	15010	2.15
Brunei Darussalam	100.00	1812.41	1720.50		83860	2.61
Bulgaria	99.79	1577.94	797.86	39.00	19450	6.79
Burkina Faso	82.58	115.60	46.35	33.50	1710	
Burundi	83.95	50.25	14.64	38.60	740	0.07
Cabo Verde	99.93	347.64	197.40		6470	2.10
Cambodia	86.18	228.57	49.84		3510	0.77
Cameroon	78.30	169.29	22.57	46.60	3490	
Canada	97.81	4718.30	3465.30	34.40	44570	2.70
Central African Republic	78.33	29.91	4.44		790	

Chad	20.92	94.95	17.92		1980	
Chile	99.73	2002.01	1170.56	46.94	22250	2.20
China	100.00	761.49	441.78	37.73	15450	3.64
Colombia	99.20	829.80	526.24	50.80	14110	1.50
Comoros		115.85	16.86	45.30	2700	
Congo	95.03	263.29	111.31		5410	
Congo (DRC)	83.05	34.49	4.23		850	
Costa Rica	93.78	1248.55	933.38	48.70	15570	1.13
Cote d’Ivoire	73.60	162.64	41.92	41.26	3650	
Croatia	99.90	1705.21	1334.27	31.53	23740	5.91
Cuba	99.90	2457.67	2202.08			4.68
Cyprus	99.04	2270.83	958.32	32.60	33000	3.16
Czechia	99.89	2484.63	2034.38	25.91	32950	6.28
Denmark	94.40	5092.98	4284.34	29.23	51990	2.47
Djibouti		122.08	55.87	42.24		1.40
Dominica	96.00	580.66	373.11		10990	3.80
Dominican Republic	99.36	936.82	428.36	45.70	14910	1.96
Ecuador	96.70	942.89	482.68	45.00	11020	1.53
Egypt	95.70	516.34	151.29	28.49	11140	0.32
El Salvador	99.90	599.55	386.51	40.00	7290	1.34
Equatorial Guinea		838.74	197.22		20330	3.30
Eritrea		55.33	16.17		2444	
Estonia	99.40	1987.72	1499.00	33.88	30200	5.56
Eswatini	91.45	663.25	459.66		10210	
Ethiopia	27.70	69.52	19.20	35.36	1740	1.95
Fiji	99.93	313.17	200.12	34.48	9270	2.64
Finland	99.80	4112.05	3181.09	26.90	44330	4.03
France	97.40	4782.29	3964.32	32.49	42840	6.04
Gabon		555.63	358.87	38.00	16450	
Gambia	58.30	74.31	13.80	34.36	1530	1.10
Georgia	99.96	797.18	291.38	36.60	9500	2.08
Germany	98.62	5463.33	4625.85	32.49	50910	8.30
Ghana	77.65	189.37	72.64	43.50	4060	0.90
Greece		2261.16	1373.51	36.71	27270	4.16
Grenada	99.30	745.10	308.04		12580	4.34
Guatemala	68.90	462.41	172.08	48.30	7780	0.60
Guinea	62.70	107.72	13.25		2130	
Guinea-Bissau	46.00	97.97	43.35		1690	
Guyana	82.49	332.67	196.06		7880	1.44
Haiti	42.73	95.44	14.64		1800	0.70
Honduras		400.34	183.79	50.00	4360	0.70
Hong Kong					60230	
Hungary	98.86	1963.16	1293.00	33.15	26200	7.00
Iceland	97.90	4245.11	3460.19	29.59	50320	3.20
India	81.40	241.48	61.40	36.45	6560	
Indonesia	92.59	362.72	162.25	38.60	11230	1.33
Iran	100.00	1563.75	852.64	40.00	20210	1.13
Iraq		472.41	87.99		17690	1.37
Ireland	99.70	5299.65	3819.28	31.57	57920	2.80

Israel		2843.04	1776.92	38.90	37170	3.21
Italy	99.90	3427.31	2552.12	35.45	39140	3.14
Jamaica	100.00	535.66	324.40		8340	1.70
Japan	99.90	4592.43	3838.61		42500	13.00
Jordan	99.70	494.75	312.81	37.00	8910	1.64
Kazakhstan	99.82	858.77	504.87	27.20	22930	6.13
Kenya	69.00	143.54	51.93	40.80	3100	
Kiribati		249.84	153.62		4300	1.91
Korea (Republic of)	99.99	2711.74	1604.13	30.92	37240	10.90
Kuwait	99.33	2899.26	2432.15		85900	2.23
Kyrgyzstan	98.89	240.23	93.94	26.80	3380	4.23
Laos	46.30	154.63	50.10		6190	3.10
Latvia	99.90	1589.69	868.49	34.01	25770	4.38
Lebanon		1147.37	598.15		12490	2.90
Lesotho	84.46	242.73	154.88		3580	
Liberia	61.10	133.15	18.97	35.30	1160	1.40
Libya	99.90	898.97	563.26		15390	3.70
Liechtenstein						
Lithuania	100.00	1978.27	1297.79	38.20	29070	7.09
Luxembourg		6374.20	5176.18	32.29	71350	4.70
Madagascar	44.60	90.43	43.09	43.00	1450	
Malawi	89.80	115.16	32.30	44.70	1220	
Malaysia	99.19	1052.55	531.24	39.96	27390	1.90
Maldives	97.43	1628.54	1181.67		12930	
Mali	55.72	81.18	25.65		2070	0.10
Malta	99.80	3511.14	2215.91	28.74	35140	3.61
Marshall Islands	100.00	934.44	491.91		4940	2.70
Mauritania	70.35	163.92	60.08	31.57	3890	
Mauritius	99.80	1206.74	532.32		22880	3.57
Median	97.97	767.77	373.11	36.70	12150	2.80
Mexico	98.03	971.82	506.79	48.30	18300	1.49
Micronesia (Federated States of)	100.00	431.59	120.15	40.10	3930	
Moldova (Republic)	99.64	480.38	234.39	26.30	6790	5.88
Mongolia	98.32	466.69	264.50	32.30	11140	8.70
Montenegro	98.48	1333.93	1000.71	32.54	18020	4.00
Morocco	71.10	465.70	218.21	39.50	7740	0.91
Mozambique	52.63	61.65	32.88	54.00	1230	
Myanmar	60.20	291.09	58.48	38.10	5570	
Namibia	88.20	969.26	599.92	58.78	11000	
Nepal	58.00	155.97	28.98		2680	
Netherlands		5251.24	4252.27	27.97	50580	7.50
New Zealand	96.38	3664.72	2882.45		37870	3.55
Nicaragua		484.53	297.26	47.12	5260	0.90
Niger	43.16	61.43	14.92	34.30	960	0.30
Nigeria	40.39	213.74	27.84		5760	
Norway	99.10	6203.45	5281.01	28.20	60600	4.50
Oman	97.97	2826.85	2519.90		41690	1.50
Pakistan	62.26	144.12	40.21	31.60	5280	0.60

Palau	100.00	1891.92	1130.69		17660	4.20
Palestine *	99.90			33.70	5670	
Panama	94.60	1750.30	1148.23	50.40	20890	2.30
Papua New Guinea		92.27	64.59		4110	
Paraguay	95.50	767.77	396.34	47.90	11790	1.30
Peru	92.40	681.00	436.34	43.60	12850	1.55
Philippines	81.75	342.29	107.97	44.47	9370	1.60
Poland	99.80	1784.40	1243.75	30.80	26640	6.50
Portugal	98.83	2778.42	1843.59	35.90	30330	3.40
Qatar	100.00	3926.12	3204.81		122670	1.18
Romania	96.98	1152.18	900.86	36.01	23240	5.89
Russian Federation	99.59	1329.29	757.03	35.60	23410	7.60
Rwanda	97.04	130.38	44.17	43.70	1930	
Saint Kitts and Nevis	100.00	1479.57	638.73		27960	
Saint Lucia	97.07	677.40	284.51	51.20	12030	1.22
Saint Vincent and the Grenadines	99.00	409.14	314.05		12240	3.04
Samoa	83.18	352.80	269.47	38.82	6260	
Sao Tome and Principe	96.82	196.90	78.55		3200	
Saudi Arabia	98.00	3117.23	2113.53		55480	2.49
Senegal	58.60	141.69	48.98		3260	
Serbia	98.53	1322.56	767.15	39.58	14760	5.92
Seychelles	99.00	1122.56	1077.36	46.80	25560	2.85
Sierra Leone	72.90	244.04	27.27		1330	
Singapore	99.60	4083.75	2226.67		85090	1.97
Slovakia	98.31	2172.16	1734.24	27.50	30320	5.51
Slovenia	99.90	2772.23	2003.98	26.98	32310	4.60
Solomon Islands	86.20	117.76	81.52	37.10	2140	
South Africa	96.70	1071.35	575.63	63.06	12880	
South Sudan *					1550	
Spain		3259.80	2322.22	36.51	36750	3.00
Sri Lanka	99.95	491.49	211.80	39.80	12030	3.60
Sudan	80.05	297.86	58.04		4260	0.89
Suriname	78.00	907.60	629.60		13810	6.10
Sweden		5386.73	4498.22	29.30	49420	2.60
Switzerland		7867.39	4939.04	32.33	64680	6.34
Syrian Arab Republic		174.30	77.56			1.50
Tajikistan	94.73	208.51	59.63	34.53	3530	4.80
Tanzania	63.70	111.98	45.49		2860	
Thailand	99.10	635.02	496.18	36.90	16160	
The FYR of Macedonia	99.90	934.58	594.07	34.37	14220	4.40
Timor-Leste	56.70	121.68	67.85	28.70	7390	5.90
Togo	44.95	99.90	20.03	42.37	1640	
Tonga	94.50	311.43	205.22	37.62	6130	3.20
Trinidad and Tobago	100.00	2180.52	1151.15		31150	3.00
Tunisia		806.34	456.68	32.20	11410	2.26

Turkey	99.71	1089.25	854.43	41.90	25870	2.70
Turkmenistan	100.00	1116.86	207.07		16450	7.40
Uganda	74.20	117.11	19.39	42.80	1870	1.10
Ukraine	99.90	534.19	226.56	25.00	8210	8.81
United Arab Emirates	99.90	2546.19	1845.41		72810	0.46
United Kingdom		4177.82	3351.67	32.31	41900	2.80
United States	98.86	9869.74	8077.93	41.50	58960	2.90
Uruguay	99.03	1958.90	1404.41	39.70	20750	3.48
Uzbekistan	100.00	416.90	192.31		6420	3.61
Vanuatu	89.40	116.09	62.54		2970	
Venezuela	96.20	947.99	357.15		18272	0.66
Viet Nam	95.06	356.28	168.99	35.30	6100	2.30
Yemen	75.60	151.40	16.49	36.70	2820	0.70
Zambia	63.30	175.18	67.08	57.40	3910	2.30
Zimbabwe	83.71	185.05	86.05		2460	

* The countries lack values for domestic general government health expenditure per capita, but since they are important aid recipients, we included them in our ranking by using GNI per capita as an alternative for the missing indicator (Spearman's correlation of the two indicators is 0.95)

Countries	Immuni-zation, DPT (% of children ages 12-23 months)	Incidence of HIV (per 1,000 uninfected population ages 15-49)	Incidence of malaria (per 1,000 population at risk)	Incidence of tuberculosis (per 100,000 people)	Nurses and midwives (per 1,000 people)	Out-of-pocket expenditure (% of current health expenditure)
Afghanistan	66	0.04	23	189	0.25	77.40
Albania	98		0	16	3.60	57.98
Algeria	91	0.05	0	70	2.24	30.88
Andorra	98		0	6	4.14	41.70
Angola	55	1.7	155.66	362		35.21
Antigua and Barbuda	92		0	3.4	3.12	32.19
Argentina	92	0.3	0	27	2.99	15.80
Armenia	94	0.1	0	44	5.49	80.65
Australia	94	0.08	0	6.6	12.66	18.94
Austria	87		0	8.2	8.18	18.92
Azerbaijan	97		0	66	6.96	78.92
Bahamas	94	1	0	26	3.70	27.72
Bahrain	99		0	12	2.51	27.99
Bangladesh	98	0.01	1.78	221	0.26	71.89
Barbados	97	1.1	0	1.2	5.86	45.18
Belarus	98	0.5	0	42	11.28	35.80
Belgium	98		0	10	11.10	15.86
Belize	95	1.4	0.02	38	1.64	22.87
Benin	76	0.62	368.57	59	0.61	43.48
Bhutan	98	0.2	0.03	178	1.42	20.13
Bolivia	87	0.2	1.6	114	0.74	28.02
Bosnia and	78	0.01	0	32	6.24	28.68

Herzegovina						
Botswana	95	8.3	0.77	326	3.30	5.25
Brazil	89		3.17	42	7.39	43.56
Brunei Darussalam	99		0	66	6.60	5.07
Bulgaria	92	0.08	0	27	5.31	47.95
Burkina Faso	91	0.2	411.62	51	0.57	31.39
Burundi	94	0.2	195.1	118	0.68	30.51
Cabo Verde	96	0.3	0.34	137	1.23	26.01
Cambodia	93	0.1	11.44	345	0.95	58.56
Cameroon	85	2	306.16	203	2.24	69.50
Canada	91		0	5.5	9.91	14.62
Central African Republic	47	2.3	387.55	407	0.22	43.08
Chad	41	0.6	188.18	153	0.36	61.16
Chile	95	0.5	0	16	0.86	34.77
China	99		0	64	2.31	35.91
Colombia	91	0.2	10.69	32	1.20	20.16
Comoros	91	0.01	1.44	35	1.21	73.13
Congo	71	1.7	201.08	378		49.72
Congo (DRC)	79	0.4	310.59	323	0.52	37.43
Costa Rica	97	0.3	0	9.5	0.80	22.14
Cote d’Ivoire	85	1.3	140.1	153	0.47	40.15
Croatia	93	0.04	0	12	8.11	15.36
Cuba	99	0.3	0	6.8	8.22	10.31
Cyprus	97		0	5.6	5.25	44.92
Czechia	96	0.07	0	5.5	8.41	15.02
Denmark	94	0.05	0	5.9	10.30	13.71
Djibouti	68	0.8	0.02	335	0.54	25.77
Dominica	99		0	7.8	5.90	29.15
Dominican Republic	87	0.5	0.15	50	0.49	44.62
Ecuador	83	0.3	2.49	40	1.20	40.48
Egypt	95	0.05	0	14	1.38	61.99
El Salvador	93	0.2	0.01	60	2.28	27.16
Equatorial Guinea	19	6.6	349.86	181	0.50	72.83
Eritrea	95	0.3	17.47	74		59.06
Estonia	93	0.5	0	16	6.45	22.69
Eswatini	90	19.2	0.93	332	1.48	9.90
Ethiopia	73	0.44	42.04	177	0.75	37.42
Fiji	99		0	43	2.93	20.64
Finland	92	0.07	0	4.7	14.72	20.35
France	96	0.2	0	8.7	9.69	9.76
Gabon	75	1.8	169.11	533	2.58	22.51
Gambia	95	1.9	124.59	174	1.63	23.59
Georgia	92	0.3	0	92	4.03	55.60
Germany	93	0.07	0	8.1	13.20	12.41
Ghana	93	1.1	271.32	156	1.55	37.82
Greece	99		0	4.2	3.37	34.34
Grenada	96		0	6.4	3.14	57.78

Guatemala	80	0.2	0.49	24	0.93	53.34
Guinea	45	0.9	338.65	176	0.38	49.76
Guinea-Bissau	88	2.3	58.07	374	1.37	35.40
Guyana	97	0.9	28.59	93	1.29	35.06
Haiti	64	1.2	3.62	188	0.82	41.73
Honduras	94	0.1	0.72	40	1.70	45.01
Hong Kong			0	69		
Hungary	99	0.04	0	8.7	6.64	29.70
Iceland	91	0.1	0	2.1	15.14	16.87
India	88		10.2	211	2.10	64.58
Indonesia	79	0.3	4.95	322	1.30	37.34
Iran	99	0.09	0.1	14	1.64	38.79
Iraq	73		0	43	1.94	78.48
Ireland	95	0.1	0	7.1	14.29	12.99
Israel	94	0.11	0	3.5	5.20	22.97
Italy	94	0.1	0	7.3	5.96	23.11
Jamaica	99	1.4	0	4.5	1.62	22.40
Japan	99	0.02	0	16	11.52	13.45
Jordan	98	0.01	0	5.5	1.89	27.98
Kazakhstan	82	0.2	0	72	8.49	35.56
Kenya	89	1.83	71.23	348	1.54	27.71
Kiribati	81		0	566	4.83	0.09
Korea (Republic of)	98		0.17	77	6.86	33.31
Kuwait	99	0.07	0	24	6.97	16.11
Kyrgyzstan	96	0.2	0	144	7.18	57.59
Laos	66	0.2	8.01	175	0.98	46.44
Latvia	98	0.4	0	37	4.82	44.56
Lebanon	83	0.04	0	12	2.48	32.14
Lesotho	93	16.6	0	724		18.89
Liberia	79	0.8	194.75	308	0.11	47.26
Libya	97	0.1	0	40	6.68	40.35
Liechtenstein			0			
Lithuania	94		0	53	7.92	32.34
Luxembourg	99	0.2	0	5.8	12.24	11.23
Madagascar	77	0.3	67.97	237	0.11	22.36
Malawi	84	5.1	233.45	159	0.25	11.39
Malaysia	95	0.3	0.21	92	4.07	37.60
Maldives	99		0	49	3.95	19.10
Mali	69	1.2	383.59	56	0.38	35.28
Malta	97		0	13	8.95	34.78
Marshall Islands	71		0	422	4.74	9.00
Mauritania	74	0.06	69.4	102	0.97	50.90
Mauritius	96	1.2	0	12	3.43	48.16
Median	93.5	0.2	0	48.5	2.92	31.17
Mexico	93	0.15	0.2	22	2.90	40.38
Micronesia (Federated States of)	69		0	177	5.44	2.63
Moldova (Republic)	89	0.44	0	101	3.38	46.29

Mongolia	99	0.02	0	428	3.98	35.87
Montenegro	89	0.11	0	16	5.65	24.08
Morocco	99	0.05	0	103	0.89	48.62
Mozambique	80	11.04	338.3	551	0.40	7.67
Myanmar	90	0.4	8.34	361	1.04	73.98
Namibia	85	5.7	21.14	446		7.72
Nepal	87	0.06	0.33	154	2.03	55.44
Netherlands	95	0.06	0	5.9	11.10	11.45
New Zealand	92	0.07	0	7.3	10.92	13.58
Nicaragua	98	0.1	2.93	48	1.38	32.22
Niger	80	0.2	360.75	93	0.29	58.51
Nigeria	57	1.02	281.5	219	1.47	75.21
Norway	96	0.06	0	6.1	17.98	14.52
Oman	99	0.1	0	9	4.47	5.91
Pakistan	75	0.2	6.33	268	0.54	65.23
Palau	98		0	123	5.53	14.45
Palestine			0	1		
Panama	86	0.6	0.21	56	1.41	27.43
Papua New Guinea	72	0.4	181.71	432	0.79	7.85
Paraguay	92	0.3	0	42	0.87	37.86
Peru	89	0.2	5.69	117	1.35	28.29
Philippines	86	0.2	0.27	554	0.24	53.94
Poland	98		0	18	5.72	22.94
Portugal	98	0.2	0	20	6.37	27.75
Qatar	98		0	23	6.60	8.55
Romania	89	0.1	0	74	6.10	20.75
Russian Federation	97		0	64	8.62	40.48
Rwanda	98	0.7	554.51	61	0.71	6.38
Saint Kitts and Nevis	97		0	0	3.98	51.51
Saint Lucia	95		0	1.9	1.59	48.70
Saint Vincent and the Grenadines	99		0	6.3		20.50
Samoa	80		0	7.7	1.74	11.88
Sao Tome and Principe	96		11.2	165	2.26	14.40
Saudi Arabia	98		0.11	10	5.70	14.34
Senegal	93	0.1	54.28	122	0.31	51.77
Serbia	92	0.04	0	19	6.12	40.50
Seychelles	96		0	15	3.26	2.08
Sierra Leone	84	1	378.04	304	0.93	41.55
Singapore	97	0.06	0	50	7.21	31.17
Slovakia	96	0.04	0	5.9	9.17	17.83
Slovenia	94		0	6.5	9.68	12.00
Solomon Islands	94		142.31	84	2.13	4.60
South Africa	76	10.6	0.77	618	5.13	7.75
South Sudan	45	2.5	142.2	146		
Spain	97	0.15	0	12	5.53	23.83
Sri Lanka	99	0.01	0	65	2.12	50.12

Sudan	93	0.2	37.51	82	0.97	73.89
Suriname	91	1	0.92	26	3.97	21.82
Sweden	98		0	8.2	11.54	15.24
Switzerland	96		0	7.8	17.28	29.56
Syrian Arab Republic	42	0.01	0	21	1.46	54.06
Tajikistan	96	0.2	0	85	5.15	66.06
Tanzania	97	2.8	113.68	287	0.33	21.89
Thailand	99	0.2	1.03	160	2.78	12.11
The FYR of Macedonia	95	0.04	0	16	3.72	35.41
Timor-Leste	79		0.69	498	1.42	8.88
Togo	89	1.28	376.39	46	0.68	50.42
Tonga	78		0	8.6	3.93	10.98
Trinidad and Tobago	97		0	18	3.23	40.08
Tunisia	98	0.04	0	38	2.64	39.90
Turkey	98		0	18	2.63	16.47
Turkmenistan	98		0	46	4.63	76.19
Uganda	93	3.3	203.09	201	1.02	40.32
Ukraine	19	0.6	0	87	7.91	54.34
United Arab Emirates	99		0	0.79	5.59	18.57
United Kingdom	94		0	9.9	8.33	15.12
United States	95		0	3.1	10.00	11.09
Uruguay	95	0.4	0	29	6.28	17.37
Uzbekistan	99	0.2	0	76	11.88	52.25
Vanuatu	81		15.47	56	1.39	8.42
Venezuela	84		28.17	32		39.96
Viet Nam	96	0.1	0.07	133	1.43	44.57
Yemen	71	0.07	37.56	48	0.74	79.37
Zambia	91	6.09	204.19	376	0.89	12.12
Zimbabwe	90	5.58	58.2	233	1.20	21.24

Countries	Income share held by lowest 20%	Income share held by second 20%	Income share held by lowest 40% **	People using at least basic drinking water services (% of population)	People using at least basic sanitation services (% of population)	Physicians (per 1,000 people)
Afghanistan				64.29	42.05	0.28
Albania	8.90	13.30	22.20	91.02	97.70	1.20
Algeria				93.52	87.54	1.83
Andorra				100.00	100.00	3.40
Angola				55.08	48.63	0.20
Antigua and Barbuda				96.74	87.50	2.76

Argentina	4.90	9.70	14.60	99.08	94.26	3.96
Armenia	7.90	12.10	20.00	99.90	93.41	2.90
Australia	6.70	12.14	18.84	99.97	99.99	3.59
Austria	7.81	13.20	21.01	100.00	99.97	5.14
Azerbaijan				90.71	92.48	3.45
Bahamas				98.89	94.93	1.98
Bahrain				100.00	100.00	0.94
Bangladesh	8.60	12.40	21.00	96.88	47.01	0.48
Barbados				98.48	96.86	2.39
Belarus	9.90	14.40	24.30	96.47	97.78	4.07
Belgium	8.57	14.12	22.69	100.00	99.49	3.32
Belize				97.58	87.53	1.14
Benin	2.48	9.60	12.08	66.32	16.35	0.16
Bhutan	6.70	10.80	17.50	97.21	68.28	0.37
Bolivia	3.90	9.50	13.40	92.18	58.80	1.61
Bosnia and Herzegovina				96.15	95.34	2.26
Botswana	4.08	7.22	11.30	89.40	76.02	0.37
Brazil	3.20	7.30	10.50	97.85	87.43	2.06
Brunei Darussalam				99.90	96.35	1.62
Bulgaria	5.39	11.55	16.94	99.15	85.99	3.99
Burkina Faso	8.94	12.10	21.04	48.27	19.13	0.06
Burundi	6.90	11.00	17.90	60.20	45.85	0.05
Cabo Verde				86.49	72.25	0.77
Cambodia				76.95	56.60	0.24
Cameroon	4.50	8.50	13.00	60.16	38.85	0.14
Canada	6.00	12.20	18.20	99.41	99.32	2.57
Central African Republic				46.33	25.32	0.07
Chad				38.85	8.58	0.05
Chile	5.01	9.01	14.02	99.62	100.00	1.08
China	6.61	10.84	17.45	92.30	83.24	1.79
Colombia	3.90	8.00	11.90	96.96	88.59	2.00
Comoros	4.50	9.10	13.60	80.15	35.83	0.14
Congo				72.19	19.55	0.22
Congo (DRC)				42.98	20.43	0.09
Costa Rica	4.20	8.30	12.50	99.70	97.55	1.15
Cote d’Ivoire	5.70	10.26	15.96	72.76	31.35	0.23
Croatia	7.24	12.84	20.08	99.59	96.51	3.00
Cuba				95.32	92.81	7.48
Cyprus	8.20	11.82	20.02	99.61	99.20	1.95
Czechia	9.76	14.67	24.44	99.88	99.13	4.31
Denmark	9.05	13.68	22.73	100.00	99.60	4.46
Djibouti	5.31	1.00	6.31	75.60	62.35	0.22
Dominica				96.79	77.89	1.08
Dominican Republic	4.90	9.00	13.90	96.58	83.54	1.57
Ecuador	4.70	9.40	14.10	93.68	87.18	2.05
Egypt	9.34	13.88	23.22	99.03	94.08	0.81
El Salvador	5.90	10.60	16.50	97.06	87.23	1.57

Equatorial Guinea				64.43	66.25	0.40
Eritrea				51.85	11.94	
Estonia	7.29	12.29	19.58	99.71	99.14	3.47
Eswatini				68.95	58.37	0.08
Ethiopia	7.30	12.00	19.30	40.04	7.09	0.09
Fiji	8.04	11.60	19.64	93.74	95.07	0.84
Finland	9.40	14.06	23.46	100.00	99.45	3.81
France	7.94	12.83	20.77	100.00	98.65	3.23
Gabon	6.00	10.80	16.80	85.63	47.37	0.36
Gambia	7.74	11.96	19.70	77.83	39.12	0.10
Georgia	6.70	11.50	18.20	98.17	90.25	5.10
Germany	7.59	12.87	20.46	100.00	99.22	4.21
Ghana	4.70	9.60	14.30	80.44	17.81	0.13
Greece	5.89	11.63	17.52	100.00	98.98	4.59
Grenada				95.63	91.49	1.45
Guatemala	4.50	8.60	13.10	93.72	65.02	0.48
Guinea				62.11	21.89	0.08
Guinea-Bissau				66.51	20.42	2.20
Guyana				95.54	85.76	0.73
Haiti				65.02	33.60	0.21
Honduras	3.20	7.80	11.00	94.29	80.24	0.61
Hong Kong				100.00	96.46	
Hungary	7.63	12.93	20.56	99.97	97.99	3.23
Iceland	9.66	13.14	22.81	100.00	98.78	3.89
India	7.60	11.45	19.05	91.86	56.94	0.76
Indonesia	6.90	10.60	17.50	88.66	71.25	0.28
Iran	6.10	10.50	16.60	95.20	88.36	1.41
Iraq				95.61	92.43	0.84
Ireland	8.16	12.98	21.14	97.38	91.15	2.95
Israel	5.20	10.70	15.90	100.00	100.00	3.22
Italy	5.82	12.07	17.89	99.44	98.77	4.03
Jamaica				90.62	87.32	0.46
Japan				98.97	99.90	2.41
Jordan	7.60	11.20	18.80	98.97	97.43	1.41
Kazakhstan	9.80	13.60	23.40	95.04	97.81	3.29
Kenya	6.20	10.30	16.50	58.28	29.30	0.20
Kiribati				70.35	46.59	0.28
Korea (Republic of)	7.42	13.20	20.62	99.68	100.00	2.31
Kuwait				100.00	100.00	2.58
Kyrgyzstan	10.00	13.90	23.90	87.43	96.52	1.88
Laos				79.94	71.93	0.40
Latvia	6.93	12.43	19.36	98.57	91.78	3.19
Lebanon				92.60	96.92	2.25
Lesotho				68.63	40.77	
Liberia	7.20	11.60	18.80	72.45	16.83	0.04
Libya				98.53	100.00	2.09
Liechtenstein				100.00	99.95	
Lithuania	6.21	11.41	17.62	97.07	92.81	4.34
Luxembourg	7.47	12.39	19.86	99.91	97.61	2.92

Madagascar	4.90	9.60	14.50	53.18	10.12	0.15
Malawi	6.40	9.80	16.20	67.91	25.90	0.02
Malaysia	6.07	10.41	16.48	96.72	99.56	1.48
Maldives				99.24	99.21	1.04
Mali				76.58	37.75	0.14
Malta	8.53	13.43	21.96	100.00	99.96	3.83
Marshall Islands				87.36	83.23	0.60
Mauritania	7.77	12.77	20.53	68.83	45.93	0.12
Mauritius				99.87	95.51	2.02
Median	6.85	11.50	18.27	95.61	88.73	1.41
Mexico	4.90	8.80	13.70	98.88	90.30	2.25
Micronesia (Federated States of)	5.50	10.70	16.20	78.57	88.31	
Moldova (Republic)	10.00	14.10	24.10	88.69	75.83	3.12
Mongolia	8.00	12.40	20.40	82.80	58.46	2.89
Montenegro	8.22	12.03	20.25	97.05	97.75	2.33
Morocco	6.70	10.70	17.40	86.64	88.42	0.63
Mozambique	4.20	7.60	11.80	53.44	28.11	0.05
Myanmar	7.30	11.30	18.60	80.84	64.71	0.62
Namibia	2.72	5.82	8.53	82.22	34.21	
Nepal				88.35	58.87	0.60
Netherlands	8.86	13.89	22.75	100.00	97.72	3.51
New Zealand				100.00	100.00	3.03
Nicaragua	5.02	9.04	14.06	81.50	74.39	0.91
Niger	7.80	11.20	19.00	49.50	13.16	0.05
Nigeria				70.03	38.41	0.31
Norway	8.88	14.03	22.91	100.00	98.06	4.49
Oman				91.76	100.00	2.02
Pakistan	8.80	12.18	20.98	91.14	58.26	0.84
Palau				100.00	100.00	1.09
Palestine	7.30	11.90	19.20	96.48	96.93	
Panama	3.30	8.00	11.30	95.98	82.23	1.57
Papua New Guinea				40.73	13.54	0.05
Paraguay	4.50	8.60	13.10	98.57	88.73	0.94
Peru	4.60	9.70	14.30	90.59	73.85	1.27
Philippines	5.67	9.27	14.93	93.07	75.40	1.33
Poland	7.30	12.80	20.10	99.38	98.38	2.40
Portugal	6.47	12.11	18.58	99.91	99.57	3.34
Qatar				99.63	100.00	2.78
Romania	4.83	11.53	16.36	100.00	83.56	2.26
Russian Federation	6.88	11.53	18.42	96.96	90.06	4.01
Rwanda	6.00	9.80	15.80	56.98	65.41	0.14
Saint Kitts and Nevis				99.02	91.61	2.52
Saint Lucia	3.10	7.90	11.00	98.16	88.36	
Saint Vincent and the Grenadines				95.15	87.18	
Samoa	7.04	11.76	18.80	97.30	98.12	0.34
Sao Tome and				84.20	42.83	0.32

Principe						
Saudi Arabia				99.86	99.91	2.39
Senegal				79.46	50.78	0.07
Serbia	4.80	11.10	15.90	85.53	97.60	3.13
Seychelles	5.40	9.80	15.20	96.25	100.00	0.95
Sierra Leone				59.56	15.29	0.04
Singapore				100.00	100.00	2.31
Slovakia	8.27	14.27	22.54	99.79	97.93	2.46
Slovenia	9.73	14.40	24.13	99.53	99.11	3.00
Solomon Islands	7.00	11.40	18.40	68.54	32.75	0.20
South Africa	2.33	4.74	7.07	92.27	74.82	0.80
South Sudan				40.81	10.44	
Spain	5.52	11.64	17.16	99.93	99.90	4.07
Sri Lanka	7.00	10.70	17.70	88.84	95.11	1.06
Sudan				60.22	36.49	0.41
Suriname				94.52	84.14	1.11
Sweden	8.24	13.83	22.07	100.00	99.30	5.40
Switzerland	7.77	12.50	20.26	100.00	99.89	4.24
Syrian Arab Republic				97.06	91.40	1.22
Tajikistan	7.23	11.88	19.12	79.63	96.58	1.76
Tanzania				54.85	28.39	0.04
Thailand	7.30	11.10	18.40	99.37	98.40	0.45
The FYR of Macedonia	6.06	12.19	18.26	93.15	98.70	2.87
Timor-Leste	9.40	13.40	22.80	76.66	52.42	0.67
Togo	5.05	9.70	14.75	64.02	15.71	0.07
Tonga	6.82	11.47	18.28	99.91	93.45	0.50
Trinidad and Tobago				98.18	93.40	2.85
Tunisia	8.02	12.44	20.46	95.99	90.88	1.27
Turkey	5.70	9.90	15.60	98.88	97.25	1.76
Turkmenistan				98.70	98.27	2.22
Uganda	6.10	9.80	15.90	47.67	18.45	0.08
Ukraine	10.10	14.40	24.50	93.72	96.22	3.49
United Arab Emirates				97.41	98.58	2.39
United Kingdom	7.52	12.07	19.59	100.00	99.11	2.80
United States	5.00	10.20	15.20	99.26	99.97	2.59
Uruguay	5.80	10.50	16.30	99.32	96.40	3.93
Uzbekistan				97.68	100.00	2.37
Vanuatu				90.66	36.09	0.17
Venezuela				95.78	93.94	
Viet Nam	6.90	11.90	18.80	93.99	81.86	0.82
Yemen	7.30	11.50	18.80	63.32	58.77	0.31
Zambia	2.72	5.84	8.56	59.24	26.09	0.09
Zimbabwe				64.51	36.89	0.08

** The values for the indicator are calculated by summing the income share held by the lowest and second 20% of population

Countries	Poverty gap at $1.90 a day (2011 PPP) (%)	Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population)	Tax revenue (% of GDP)	Total debt service (% of GNI)	Mean years of schooling
Afghanistan			8.84	0.31	3.6
Albania	0.30	1.80	17.59	4.89	10
Algeria				0.22	8
Andorra					10.2
Angola			9.73	10.04	5.1
Antigua and Barbuda					9.2
Argentina	0.30	0.70	12.10	4.75	9.9
Armenia	0.30	1.80	21.28	13.67	11.7
Australia	0.56	0.76	22.25		12.9
Austria	0.33	0.50	25.52		12.1
Azerbaijan			14.56	4.99	10.7
Bahamas			14.16		11.1
Bahrain					9.4
Bangladesh	2.70	14.80	8.77	0.76	5.2
Barbados			24.57		10.6
Belarus	0.00	0.00	13.79	13.66	12.3
Belgium	0.00	0.00	23.07		11.8
Belize			25.59	5.81	10.5
Benin	23.25	48.60		1.09	3.6
Bhutan	0.24	1.64	12.49	5.44	3.1
Bolivia	3.00	7.10		2.33	8.9
Bosnia and Herzegovina			19.95	6.35	9.7
Botswana	4.05	15.75	20.85	1.12	9.3
Brazil	1.60	4.30	12.77	6.68	7.8
Brunei Darussalam					9.1
Bulgaria	0.50	1.12	20.04	15.30	11.8
Burkina Faso	7.52	39.06	16.66	1.17	1.5
Burundi	30.40	71.80		1.13	3
Cabo Verde			18.60	2.75	6.1
Cambodia			14.83	3.95	4.7
Cameroon	7.60	23.80	12.07	2.89	6.3
Canada	0.30	0.80	12.46		13.1
Central African Republic			6.94	1.37	4.3
Chad				1.41	2.3
Chile	0.83	0.68	17.40		10.3
China	0.20	0.70	9.20	1.49	7.8
Colombia	1.80	4.50	14.96	5.66	8.3
Comoros	6.20	17.90		0.38	4.8
Congo			15.08	1.78	6.3
Congo (DRC)				1.34	6.6
Costa Rica	0.50	1.30	13.91	5.17	8.8

Cote d'Ivoire	8.91	28.07	15.71	4.46	5.1
Croatia	0.49	0.67	21.40		11.3
Cuba					11.6
Cyprus	0.00	0.00	24.00		12.1
Czechia	0.00	0.00	14.68		12.7
Denmark	0.05	0.16	33.45		12.6
Djibouti	6.17	18.22		9.92	4.1
Dominica				4.78	7.8
Dominican Republic	0.50	1.60	13.51	5.02	7.8
Ecuador	1.20	3.60		5.48	8.7
Egypt	0.20	1.30	11.56	2.02	7.2
El Salvador	0.50	2.20	17.38	6.13	6.9
Equatorial Guinea			6.38		5.5
Eritrea				0.39	3.9
Estonia	0.46	0.49	21.83		12.6
Eswatini				1.08	6.5
Ethiopia	8.88	30.26	8.09	1.66	2.7
Fiji	0.00	0.14	23.50	1.25	10.8
Finland	0.00	0.00	20.95		12.4
France	0.00	0.00	23.20		11.5
Gabon	0.80	3.40	11.47	2.78	8.2
Gambia	1.16	7.10	18.26	2.66	3.4
Georgia	1.00	3.90	23.47	18.79	12.8
Germany	0.00	0.00	11.18		14.1
Ghana	4.70	13.30	15.43	2.81	7.1
Greece	0.55	1.74	26.65		10.8
Grenada				4.99	8.7
Guatemala	2.50	8.70	10.39	4.60	6.5
Guinea				0.75	2.6
Guinea-Bissau			10.32	0.57	3
Guyana				2.34	8.4
Haiti				1.13	5.2
Honduras	6.30	16.00	16.59	5.16	6.5
Hong Kong					12
Hungary	0.27	0.64	23.32		11.9
Iceland	0.00	0.00	37.75		12.4
India			11.09	3.40	6.4
Indonesia	1.00	6.50	10.34	7.81	8
Iran	0.00	0.30	15.48	0.50	9.8
Iraq			2.03		6.7
Ireland	0.28	0.43	19.05		12.5
Israel	0.10	0.20	23.25		13
Italy	1.21	1.96	23.52		10.2
Jamaica			26.03	14.26	9.8
Japan			11.15		12.7
Jordan		0.10	15.29	6.33	10.4
Kazakhstan	0.00	0.00	9.92	16.34	11.7
Kenya	11.60	36.80	16.18	1.65	6.4
Kiribati			24.92		7.9

Korea (Republic of)	0.02	0.30	14.83		12.1
Kuwait			1.05		7.2
Kyrgyzstan	0.20	1.40	16.95	6.89	10.9
Laos				3.68	5.2
Latvia	0.50	0.85	23.80		12.8
Lebanon			13.50	29.73	8.6
Lesotho			26.65	2.19	6.3
Liberia	13.00	40.90		0.41	4.5
Libya					7.3
Liechtenstein					12.5
Lithuania	0.57	0.35	16.95		13
Luxembourg	0.10	0.25	25.64		12.1
Madagascar	40.60	75.80	11.00	1.29	6.1
Malawi	29.40	70.30	15.49	1.40	4.5
Malaysia	0.00	0.00	13.76		10.2
Maldives			21.00	3.41	6.3
Mali			15.40	0.88	2.3
Malta	0.00	0.00	25.71		11.3
Marshall Islands			17.79		10.8
Mauritania	0.97	6.00		4.88	4.4
Mauritius			18.13	13.59	9.3
Median	0.50	1.40	13.54	7.53	8.6
Mexico	0.70	2.20	6.05		8
Micronesia (Federated States of)	5.50	15.40	16.25	5.00	11.6
Moldova (Republic of)	0.00	0.20	11.35	14.31	10.1
Mongolia	0.10	0.60		28.76	11.3
Montenegro	0.12	0.39	21.45	3.74	5.4
Morocco	0.20	1.00	22.24	5.14	3.5
Mozambique	26.10	60.17	6.41	1.29	4.9
Myanmar	1.50	6.20	28.59		6.8
Namibia	4.27	11.87	18.69	1.11	4.9
Nepal			21.91		12.1
Netherlands	0.00	0.00	27.39		12.5
New Zealand			16.17	6.41	6.7
Nicaragua	0.22	1.56		1.53	1.9
Niger	13.23	44.50		0.63	6.2
Nigeria			21.84		12.6
Norway	0.00	0.24			9.5
Oman				1.46	5.2
Pakistan	0.50	2.78	19.59		12.3
Palau			6.10		9.1
Palestine	0.20	1.00			10
Panama	0.50	2.20	12.95	16.37	4.6
Papua New Guinea			9.57	3.95	8.4
Paraguay	0.30	1.70	13.80	4.24	9.2
Peru	0.90	3.50	13.68	2.99	9.3
Philippines	1.17	5.97	16.37		12.2

Poland	0.15	0.57	22.40		9.2
Portugal	0.29	0.46			9.8
Qatar			16.75	10.26	11
Romania	1.90	7.54	9.14	5.73	12
Russian Federation	0.00	0.00	14.79	2.70	4.1
Rwanda	20.20	55.50	19.27		8.4
Saint Kitts and Nevis			21.19	3.04	8.9
Saint Lucia	2.70	4.70	25.73	3.90	8.6
Saint Vincent and the Grenadines			24.64	2.99	10.3
Samoa	0.10	1.10		0.82	6
Sao Tome and Principe			3.39		9.5
Saudi Arabia			15.77	2.15	2.9
Senegal			16.11	15.50	11.1
Serbia	3.24	5.23	31.67		9.5
Seychelles	0.40	1.10		1.17	3.4
Sierra Leone			13.35		11.5
Singapore			17.43		12.5
Slovakia	0.23	0.54	18.63		12.3
Slovenia	0.00	0.00	26.68	1.98	5.4
Solomon Islands	6.80	25.10	27.11	4.83	10.1
South Africa	5.30	19.41			4.8
South Sudan			13.86		9.8
Spain	0.60	1.01	12.20	4.14	10.9
Sri Lanka	0.10	0.80	7.96	0.34	3.6
Sudan					8.5
Suriname			27.76		12.4
Sweden	0.37	0.50	9.75		13.4
Switzerland	0.00	0.00			5.1
Syrian Arab Republic				7.75	10.5
Tajikistan	1.02	4.82	11.39	1.42	5.8
Tanzania			15.40	3.66	7.6
Thailand	0.00	0.00	16.95	8.49	9.6
The FYR of Macedonia	2.09	3.85	9.89	0.04	4.5
Timor-Leste	6.70	30.70	19.06	1.99	4.8
Togo	19.07	47.95	20.37	1.54	11.2
Tonga	0.18	0.98	25.44		10.9
Trinidad and Tobago			22.04	5.01	7.1
Tunisia	0.00	0.30	18.32	8.90	8
Turkey	0.00	0.20		0.12	9.8
Turkmenistan			13.46	3.57	5.7
Uganda	13.20	41.70	19.63	13.28	11.3
Ukraine	0.00	0.10	0.04		10.8
United Arab Emirates			25.48		12.9
United Kingdom	0.10	0.20	10.98		13.4

United States	1.00	1.20	23.71		8.7
Uruguay	0.00	0.10	14.15	1.66	11.4
Uzbekistan			16.65	1.12	6.8
Vanuatu				7.73	10.1
Venezuela				3.73	8.1
Viet Nam	0.40	2.00		0.45	3
Yemen	4.50	18.80	13.35	3.62	7
Zambia	29.08	56.12	15.75	6.57	8.2
Zimbabwe					

Countries	HDI label	Cluster	Normalized DALYs	1 - DALYs	Weighted sum (original weights)	Average of top 4	Aggregate
Afghanistan	Low	Lowest	0.586	0.414	0.244	0.240	0.315
Albania	High	High	0.091	0.909	0.640	0.635	0.760
Algeria	High	High	0.122	0.878	0.597	0.590	0.720
Andorra	Very high	Highest	0.031	0.969	0.754	0.748	0.852
Angola	Medium	Lowest	0.416	0.584	0.253	0.252	0.384
Antigua and Barbuda	High	High	0.105	0.895	0.630	0.624	0.747
Argentina	Very high	High	0.105	0.895	0.689	0.683	0.782
Armenia	High	High	0.117	0.883	0.692	0.689	0.780
Australia	Very high	Highest	0.029	0.971	0.824	0.822	0.893
Austria	Very high	Highest	0.031	0.969	0.832	0.829	0.896
Azerbaijan	High	High	0.207	0.793	0.635	0.632	0.708
Bahamas	Very high	High	0.155	0.845	0.698	0.694	0.766
Bahrain	Very high	High	0.126	0.874	0.700	0.692	0.778
Bangladesh	Medium	Middle	0.213	0.787	0.426	0.418	0.574
Barbados	Very high	High	0.121	0.879	0.690	0.685	0.776
Belarus	Very high	Highest	0.141	0.859	0.718	0.716	0.784
Belgium	Very high	Highest	0.039	0.961	0.828	0.824	0.890
Belize	High	High	0.191	0.809	0.650	0.646	0.723
Benin	Low	Lowest	0.438	0.562	0.181	0.179	0.317
Bhutan	Medium	Middle	0.202	0.798	0.455	0.442	0.594
Bolivia	Medium	Middle	0.183	0.817	0.516	0.514	0.648
Bosnia and Herzegovina	High	High	0.089	0.911	0.665	0.659	0.775
Botswana	High	Middle	0.401	0.599	0.566	0.563	0.581
Brazil	High	High	0.129	0.871	0.609	0.601	0.723
Brunei Darussalam	Very high	Highest	0.094	0.906	0.701	0.694	0.793
Bulgaria	Very high	High	0.128	0.872	0.690	0.688	0.775
Burkina Faso	Low	Lowest	0.556	0.444	0.075	0.072	0.179
Burundi	Low	Lowest	0.543	0.457	0.227	0.222	0.318
Cabo Verde	Medium	Middle	0.170	0.830	0.475	0.467	0.623
Cambodia	Medium	Middle	0.283	0.717	0.360	0.354	0.504
Cameroon	Medium	Lowest	0.570	0.430	0.268	0.268	0.340
Canada	Very high	Highest	0.034	0.966	0.835	0.833	0.897
Cent. Afr. Rep. ***	Low	Lowest	1.000	0.000	0.134	0.135	0.065

Chad	Low	Lowest	0.599	0.401	0.019	0.020	0.090
Chile	Very high	High	0.059	0.941	0.715	0.709	0.817
China	High	High	0.088	0.912	0.569	0.562	0.716
Colombia	High	High	0.061	0.939	0.615	0.608	0.755
Comoros	Low	Middle	0.331	0.669	0.317	0.312	0.457
Congo	Medium	Lowest	0.481	0.519	0.268	0.268	0.373
Congo (DRC)	Low	Lowest	0.536	0.464	0.148	0.154	0.267
Costa Rica	High	High	0.039	0.961	0.674	0.666	0.800
Cote d’Ivoire	Low	Middle	0.581	0.419	0.279	0.277	0.340
Croatia	Very high	Highest	0.080	0.920	0.729	0.725	0.817
Cuba	High	Highest	0.066	0.934	0.732	0.730	0.826
Cyprus	Very high	High	0.039	0.961	0.739	0.736	0.841
Czechia	Very high	Highest	0.055	0.945	0.784	0.782	0.860
Denmark	Very high	Highest	0.051	0.949	0.854	0.852	0.899
Djibouti	Low	Middle	0.355	0.645	0.360	0.352	0.476
Dominica	High	High	0.185	0.815	0.571	0.564	0.678
Dominican Republic	High	High	0.136	0.864	0.588	0.580	0.708
Ecuador	High	High	0.080	0.920	0.603	0.597	0.741
Egypt	Medium	High	0.222	0.778	0.608	0.598	0.682
El Salvador	Medium	High	0.099	0.901	0.582	0.573	0.718
Equatorial Guinea	Medium	Lowest	0.418	0.582	0.353	0.349	0.451
Eritrea	Low	Lowest	0.433	0.567	0.113	0.114	0.255
Estonia	Very high	Highest	0.084	0.916	0.765	0.763	0.836
Eswatini	Medium	Middle	0.669	0.331	0.377	0.374	0.352
Ethiopia	Low	Lowest	0.372	0.628	0.027	0.029	0.135
Fiji	High	High	0.391	0.609	0.655	0.652	0.630
Finland	Very high	Highest	0.033	0.967	0.816	0.813	0.887
France	Very high	Highest	0.023	0.977	0.821	0.817	0.894
Gabon	High	Middle	0.346	0.654	0.445	0.444	0.539
Gambia	Low	Middle	0.361	0.639	0.290	0.284	0.426
Georgia	High	High	0.149	0.851	0.700	0.699	0.771
Germany	Very high	Highest	0.045	0.955	0.891	0.891	0.923
Ghana	Medium	Middle	0.377	0.623	0.311	0.312	0.441
Greece	Very high	High	0.039	0.961	0.729	0.724	0.834
Grenada	High	High	0.210	0.790	0.618	0.612	0.695
Guatemala	Medium	Middle	0.175	0.825	0.492	0.485	0.632
Guinea	Low	Lowest	0.563	0.437	0.161	0.157	0.262
Guinea-Bissau	Low	Lowest	0.621	0.379	0.183	0.180	0.261
Guyana	Medium	High	0.291	0.709	0.593	0.586	0.645
Haiti	Low	Lowest	0.418	0.582	0.253	0.252	0.383
Honduras	Medium	Middle	0.168	0.832	0.537	0.528	0.663
Hong Kong	Very high	Highest			0.824	0.932	
Hungary	Very high	Highest	0.115	0.885	0.744	0.741	0.810
Iceland	Very high	Highest	0.023	0.977	0.823	0.820	0.895
India	Medium	Middle	0.304	0.696	0.456	0.450	0.559
Indonesia	Medium	Middle	0.219	0.781	0.515	0.510	0.631
Iran	High	High	0.138	0.862	0.645	0.640	0.743
Iraq	Medium	High	0.285	0.715	0.578	0.567	0.637

Ireland	Very high	Highest	0.042	0.958	0.803	0.802	0.877
Israel	Very high	Highest	0.024	0.976	0.785	0.783	0.874
Italy	Very high	Highest	0.020	0.980	0.752	0.746	0.855
Jamaica	High	High	0.151	0.849	0.606	0.602	0.715
Japan	Very high	Highest	0.000	1.000	0.839	0.836	0.915
Jordan	High	High	0.135	0.865	0.680	0.675	0.764
Kazakhstan	Very high	Highest	0.187	0.813	0.694	0.692	0.750
Kenya	Medium	Lowest	0.354	0.646	0.236	0.238	0.392
Kiribati	Medium	Middle	0.516	0.484	0.366	0.367	0.421
Korea (Republic of)	Very high	Highest	0.026	0.974	0.762	0.759	0.860
Kuwait	Very high	Highest	0.077	0.923	0.699	0.688	0.797
Kyrgyzstan	Medium	High	0.219	0.781	0.631	0.629	0.701
Laos	Medium	Middle	0.335	0.665	0.425	0.417	0.527
Latvia	Very high	High	0.121	0.879	0.724	0.723	0.797
Lebanon	High	Highest	0.071	0.929	0.628	0.621	0.759
Lesotho	Low	Middle	0.979	0.021	0.313	0.312	0.080
Liberia	Low	Lowest	0.457	0.543	0.225	0.224	0.348
Libya	Medium	High	0.139	0.861	0.637	0.626	0.734
Liechtenstein	Very high	Highest			0.721	0.957	
Lithuania	Very high	Highest	0.113	0.887	0.737	0.737	0.809
Luxembourg	Very high	Highest	0.030	0.970	0.867	0.864	0.915
Madagascar	Low	Lowest	0.485	0.515	0.155	0.159	0.286
Malawi	Low	Lowest	0.575	0.425	0.232	0.230	0.312
Malaysia	Very high	High	0.116	0.884	0.680	0.674	0.772
Maldives	High	High	0.069	0.931	0.639	0.626	0.764
Mali	Low	Lowest	0.540	0.460	0.261	0.253	0.341
Malta	Very high	Highest	0.037	0.963	0.767	0.763	0.857
Marshall Islands	High	Middle	0.411	0.589	0.604	0.603	0.596
Mauritania	Low	Middle	0.283	0.717	0.291	0.286	0.453
Mauritius	High	High	0.160	0.840	0.666	0.658	0.744
Mexico	High	High	0.110	0.890	0.633	0.626	0.746
Micronesia (Federated States)	Medium	Middle	0.377	0.623	0.518	0.513	0.566
Moldova (Republic of)	High	High	0.185	0.815	0.596	0.596	0.697
Mongolia	High	High	0.274	0.726	0.496	0.497	0.600
Montenegro	Very high	Highest	0.087	0.913	0.711	0.707	0.803
Morocco	Medium	Middle	0.172	0.828	0.509	0.498	0.642
Mozambique	Low	Lowest	0.582	0.418	0.158	0.157	0.256
Myanmar	Medium	Middle	0.252	0.748	0.404	0.396	0.544
Namibia	Medium	Middle	0.407	0.593	0.375	0.374	0.471
Nepal	Medium	Middle	0.244	0.756	0.418	0.410	0.557
Netherlands	Very high	Highest	0.038	0.962	0.839	0.836	0.897
New Zealand	Very high	Highest	0.039	0.961	0.810	0.807	0.881
Nicaragua	Medium	Middle	0.081	0.919	0.474	0.468	0.656
Niger	Low	Lowest	0.532	0.468	0.070	0.068	0.179
Nigeria	Low	Lowest	0.455	0.545	0.307	0.306	0.408
Norway	Very high	Highest	0.022	0.978	0.881	0.878	0.927
Oman	Very high	Highest	0.101	0.899	0.709	0.703	0.795

Pakistan	Medium	Middle	0.342	0.658	0.434	0.426	0.529
Palau	Very high	High			0.752	0.749	
Palestine	Medium	High	0.238	0.762	0.645	0.638	0.697
Panama	High	High	0.071	0.929	0.644	0.640	0.771
Papua New Guinea	Low	Lowest	0.541	0.459	0.084	0.088	0.201
Paraguay	High	High	0.147	0.853	0.620	0.613	0.723
Peru	High	High	0.064	0.936	0.561	0.557	0.722
Philippines	Medium	Middle	0.252	0.748	0.567	0.563	0.649
Poland	Very high	Highest	0.074	0.926	0.747	0.744	0.830
Portugal	Very high	Highest	0.041	0.959	0.716	0.708	0.824
Qatar	Very high	Highest	0.064	0.936	0.769	0.762	0.845
Romania	Very high	High	0.125	0.875	0.675	0.672	0.767
Russian Federation	Very high	High	0.195	0.805	0.694	0.692	0.747
Rwanda	Low	Lowest	0.315	0.685	0.289	0.284	0.441
Saint Kitts and Nevis	High	High			0.638	0.630	
Saint Lucia	High	High	0.129	0.871	0.623	0.617	0.733
Saint Vincent and the Grenadines	High	High	0.207	0.793	0.603	0.596	0.688
Samoa	High	High	0.205	0.795	0.672	0.667	0.728
Sao Tome and Principe	Medium	Middle	0.256	0.744	0.377	0.373	0.527
Saudi Arabia	Very high	Highest	0.098	0.902	0.731	0.723	0.808
Senegal	Low	Middle	0.372	0.628	0.322	0.313	0.443
Serbia	High	High	0.111	0.889	0.651	0.648	0.759
Seychelles	High	High	0.155	0.845	0.683	0.677	0.756
Sierra Leone	Low	Lowest	0.617	0.383	0.146	0.145	0.236
Singapore	Very high	Highest	0.001	0.999	0.771	0.767	0.875
Slovakia	Very high	Highest	0.090	0.910	0.768	0.765	0.835
Slovenia	Very high	Highest	0.031	0.969	0.775	0.772	0.865
Solomon Islands	Low	Middle	0.464	0.536	0.272	0.270	0.381
South Africa	Medium	Middle	0.479	0.521	0.591	0.589	0.554
South Sudan	Low	Lowest	0.597	0.403	0.080	0.084	0.184
Spain	Very high	Highest	0.013	0.987	0.743	0.736	0.852
Sri Lanka	High	High	0.082	0.918	0.637	0.634	0.763
Sudan	Low	Lowest	0.329	0.671	0.213	0.210	0.375
Suriname	High	High	0.220	0.780	0.599	0.593	0.680
Sweden	Very high	Highest	0.029	0.971	0.856	0.854	0.910
Switzerland	Very high	Highest	0.019	0.981	0.890	0.889	0.934
Syrian Arab Republic	Low	High	0.130	0.870	0.551	0.539	0.684
Tajikistan	Medium	High	0.215	0.785	0.590	0.588	0.679
Tanzania	Low	Lowest	0.422	0.578	0.207	0.209	0.348
Thailand	High	High	0.083	0.917	0.639	0.629	0.760
The FYR of Macedonia	High	High	0.133	0.867	0.653	0.647	0.749
Timor-Leste	Medium	Middle	0.206	0.794	0.344	0.338	0.518
Togo	Low	Lowest	0.486	0.514	0.192	0.192	0.314
Tonga	High	High	0.251	0.749	0.685	0.681	0.714
Trinidad and	High	High	0.185	0.815	0.701	0.697	0.753

Tobago							
Tunisia	High	High	0.109	0.891	0.594	0.584	0.722
Turkey	High	High	0.098	0.902	0.653	0.643	0.762
Turkmenistan	High	High	0.248	0.752	0.667	0.661	0.705
Uganda	Low	Lowest	0.493	0.507	0.146	0.150	0.276
Ukraine	High	Highest	0.183	0.817	0.669	0.666	0.737
United Arab Emirates	Very high	Highest	0.124	0.876	0.732	0.727	0.798
United Kingdom	Very high	Highest	0.053	0.947	0.829	0.827	0.885
United States	Very high	Highest	0.087	0.913	0.984	0.983	0.947
Uruguay	Very high	High	0.085	0.915	0.682	0.674	0.785
Uzbekistan	High	High	0.242	0.758	0.697	0.693	0.725
Vanuatu	Medium	Middle	0.436	0.564	0.400	0.397	0.473
Venezuela	High	High	0.102	0.898	0.653	0.648	0.763
Viet Nam	Medium	High	0.127	0.873	0.569	0.563	0.701
Yemen	Low	Middle	0.327	0.673	0.276	0.269	0.426
Zambia	Medium	Lowest	0.615	0.385	0.242	0.246	0.307
Zimbabwe	Low	Middle	0.592	0.408	0.317	0.321	0.362

*** The country has a value of 0 for the complement of the normalized DALYs. We set the geometric mean as the anti-log(sum of the (log +1) divided by 2) - 1

Countries	Rank	HDI Rank ****	HDI - Rank	Abs (HDI - Rank)	GNI Rank ****	GNI - Rank	Abs (GNI - Rank)
Afghanistan	166	164	-2	2	164	-2	2
Albania	67	66	-1	1	90	23	23
Algeria	92	79	-13	13	78	-14	14
Andorra	28	33	5	5		-28	
Angola	152	141	-11	11	121	-31	31
Antigua and Barbuda	76	67	-9	9	54	-22	22
Argentina	51	45	-6	6	60	9	9
Armenia	52	80	28	28	105	53	53
Australia	14	3	-11	11	19	5	5
Austria	11	18	7	7	13	2	2
Azerbaijan	98	76	-22	22	71	-27	27
Bahamas	61	51	-10	10	40	-21	21
Bahrain	53	39	-14	14	22	-31	31
Bangladesh	126	134	8	8	139	13	13
Barbados	54	55	1	1	67	13	13
Belarus	50	52	2	2	66	16	16
Belgium	15	15	0	0	18	3	3
Belize	88	101	13	13	111	23	23
Benin	165	157	-8	8	158	-7	7
Bhutan	124	131	7	7	107	-17	17
Bolivia	114	112	-2	2	116	2	2
Bosnia and Herzegovina	55	73	18	18	85	30	30
Botswana	125	98	-27	27	68	-57	57

Brazil	87	75	-12	12	76	-11	11
Brunei Darussalam	48	38	-10	10	4	-44	44
Bulgaria	56	48	-8	8	61	5	5
Burkina Faso	180	178	-2	2	168	-12	12
Burundi	164	179	15	15	181	17	17
Cabo Verde	121	120	-1	1	119	-2	2
Cambodia	137	142	5	5	145	8	8
Cameroon	163	146	-17	17	146	-17	17
Canada	9	11	2	2	20	11	11
Central African Republic	185	183	-2	2	180	-5	5
Chad	183	181	-2	2	162	-21	21
Chile	37	42	5	5	55	18	18
China	94	82	-12	12	74	-20	20
Colombia	72	85	13	13	81	9	9
Comoros	141	159	18	18	154	13	13
Congo	156	129	-27	27	129	-27	27
Congo (DRC)	172	172	0	0	179	7	7
Costa Rica	43	60	17	17	73	30	30
Cote d'Ivoire	162	165	3	3	142	-20	20
Croatia	38	44	6	6	49	11	11
Cuba	35	69	34	34		-35	
Cyprus	30	30	0	0	33	3	3
Czechia	24	25	1	1	34	10	10
Denmark	8	9	1	1	12	4	4
Djibouti	138	166	28	28			
Dominica	110	97	-13	13	100	-10	10
Dominican Republic	97	91	-6	6	77	-20	20
Ecuador	81	80	-1	1	98	17	17
Egypt	107	109	2	2	96	-11	11
El Salvador	93	115	22	22	115	22	22
Equatorial Guinea	143	135	-8	8	58	-85	85
Eritrea	176	174	-2	2	157	-19	19
Estonia	31	28	-3	3	39	8	8
Eswatini	158	137	-21	21	101	-57	57
Ethiopia	182	169	-13	13	167	-15	15
Fiji	120	89	-31	31	104	-16	16
Finland	16	14	-2	2	21	5	5
France	13	21	8	8	23	10	10
Gabon	132	105	-27	27	69	-63	63
Gambia	148	169	21	21	172	24	24
Georgia	58	68	10	10	102	44	44
Germany	4	4	0	0	14	10	10
Ghana	146	136	-10	10	137	-9	9
Greece	33	28	-5	5	43	10	10
Grenada	104	71	-33	33	87	-17	17
Guatemala	118	122	4	4	112	-6	6
Guinea	173	173	0	0	160	-13	13

Guinea-Bissau	174	171	-3	3	169	-5	5
Guyana	115	120	5	5	110	-5	5
Haiti	153	163	10	10	166	13	13
Honduras	111	128	17	17	133	22	22
Hong Kong							
Hungary	39	43	4	4	45	6	6
Iceland	12	6	-6	6	16	4	4
India	128	125	-3	3	118	-10	10
Indonesia	119	111	-8	8	95	-24	24
Iran	80	58	-22	22	59	-21	21
Iraq	117	116	-1	1	65	-52	52
Ireland	19	4	-15	15	10	-9	9
Israel	21	19	-2	2	30	9	9
Italy	26	26	0	0	27	1	1
Jamaica	95	92	-3	3	108	13	13
Japan	6	17	11	11	24	18	18
Jordan	62	90	28	28	106	44	44
Kazakhstan	74	57	-17	17	52	-22	22
Kenya	151	139	-12	12	150	-1	1
Kiribati	149	130	-19	19	134	-15	15
Korea (Republic of)	23	20	-3	3	29	6	6
Kuwait	45	53	8	8	2	-43	43
Kyrgyzstan	100	117	17	17	147	47	47
Laos	135	133	-2	2	123	-12	12
Latvia	46	41	-5	5	47	1	1
Lebanon	69	78	9	9	88	19	19
Lesotho	184	155	-29	29	143	-41	41
Liberia	159	176	17	17	177	18	18
Libya	83	110	27	27	75	-8	8
Liechtenstein							
Lithuania	40	34	-6	6	41	1	1
Luxembourg	5	24	19	19	6	1	1
Madagascar	170	154	-16	16	173	3	3
Malawi	168	166	-2	2	176	8	8
Malaysia	57	55	-2	2	42	-15	15
Maldives	63	98	35	35	83	20	20
Mali	161	177	16	16	161	0	0
Malta	25	27	2	2	32	7	7
Marshall Islands	123				132	9	9
Mauritania	142	155	13	13	141	-1	1
Mauritius	79	61	-18	18	53	-26	26
Mexico	78	70	-8	8	62	-16	16
Micronesia (Federated States of)	127	127	0	0	138	11	11
Moldova (Republic of)	103	106	3	3	117	14	14
Mongolia	122	88	-34	34	96	-26	26
Montenegro	42	48	6	6	64	22	22

Morocco	116	118	2	2	113	-3	3
Mozambique	175	175	0	0	175	0	0
Myanmar	131	143	12	12	128	-3	3
Namibia	140	124	-16	16	99	-41	41
Nepal	129	144	15	15	155	26	26
Netherlands	10	9	-1	1	15	5	5
New Zealand	18	15	-3	3	28	10	10
Nicaragua	112	119	7	7	131	19	19
Niger	181	184	3	3	178	-3	3
Nigeria	150	152	2	2	126	-24	24
Norway	3	1	-2	2	8	5	5
Oman	47	45	-2	2	26	-21	21
Pakistan	133	145	12	12	130	-3	3
Palau							
Palestine	102	112	10	10	127	25	25
Panama	59	63	4	4	56	-3	3
Papua New Guinea	178	147	-31	31	136	-42	42
Paraguay	89	104	15	15	93	4	4
Peru	90	82	-8	8	86	-4	4
Philippines	113	107	-6	6	103	-10	10
Poland	34	32	-2	2	44	10	10
Portugal	36	40	4	4	37	1	1
Qatar	29	34	5	5	1	-28	28
Romania	60	50	-10	10	51	-9	9
Russian Federation	77	47	-30	30	50	-27	27
Rwanda	145	153	8	8	163	18	18
Saint Kitts and Nevis							
Saint Lucia	84	87	3	3	91	7	7
Saint Vincent and the Grenadines	105	95	-10	10	89	-16	16
Samoa	85	100	15	15	122	37	37
Sao Tome and Principe	134	140	6	6	149	15	15
Saudi Arabia	41	36	-5	5	11	-30	30
Senegal	144	161	17	17	148	4	4
Serbia	70	63	-7	7	79	9	9
Seychelles	71	59	-12	12	48	-23	23
Sierra Leone	177	180	3	3	174	-3	3
Singapore	20	8	-12	12	3	-17	17
Slovakia	32	37	5	5	38	6	6
Slovenia	22	22	0	0	35	13	13
Solomon Islands	154	147	-7	7	159	5	5
South Africa	130	107	-23	23	84	-46	46
South Sudan	179	182	3	3	171	-8	8
Spain	27	23	-4	4	31	4	4
Sri Lanka	64	72	8	8	91	27	27
Sudan	155	161	6	6	135	-20	20
Suriname	108	96	-12	12	82	-26	26

Sweden	7	7	0	0	17	10	10
Switzerland	2	2	0	0	7	5	5
Syrian Arab Republic	106	149	43	43			
Tajikistan	109	123	14	14	144	35	35
Tanzania	160	150	-10	10	152	-8	8
Thailand	68	82	14	14	72	4	4
The FYR of Macedonia	75	77	2	2	80	5	5
Timor-Leste	136	126	-10	10	114	-22	22
Togo	167	160	-7	7	170	3	3
Tonga	96	94	-2	2	124	28	28
Trinidad and Tobago	73	63	-10	10	36	-37	37
Tunisia	91	92	1	1	94	3	3
Turkey	66	62	-4	4	46	-20	20
Turkmenistan	99	102	3	3	69	-30	30
Uganda	171	158	-13	13	165	-6	6
Ukraine	82	86	4	4	109	27	27
United Arab Emirates	44	31	-13	13	5	-39	39
United Kingdom	17	13	-4	4	25	8	8
United States	1	11	10	10	9	8	8
Uruguay	49	54	5	5	57	8	8
Uzbekistan	86	103	17	17	120	34	34
Vanuatu	139	132	-7	7	151	12	12
Venezuela	65	73	8	8	63	-2	2
Viet Nam	101	112	11	11	125	24	24
Yemen	147	168	21	21	153	6	6
Zambia	169	137	-32	32	139	-30	30
Zimbabwe	157	151	-6	6	156	-1	1

**** We adjusted the ranks of the GNIpc and HDI so that they rank only countries that have their scores available with our framework

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