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Benchmarking Approach on Food Sustainability Assessment Using Composite Indicators

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ABSTRACT: This article defines a new approach to measuring global food security and sustainability through a composite indicator developed on three layers: availability, diversity and environment, and introduces an elimination system that motivates countries to replicate their commitments to protect and revitalise the food industry. This would translate to a clearer and more focused view on the most critical issues that require urgent solutions, such as ensuring the basic needs of their populations, diversifying the existing variety of food products and nutritional values, and implementing innovative and sustainable process flows. To meet the scope, the OECD methodology was applied to the implementation of composite indicators that would rank 176 countries based on the three pillars. The results indicate the dominance of the European countries, among the other 99 eligible countries, when it comes to adopting sustainable solutions for their food industry, and efficient measures for the population and the market. The final ranking shows its representativeness compared to other existing composite indicators, as 85% of the top 20 countries are represented in at least one other existing food index.

Keywords: Bioeconomy, composite indicator, food security, nutrition, sustainability

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1. INTRODUCTION

This paper defines a new approach to measuring global commitment to achieving food security, through the UN Sustainable Development Goals. The 3 levels are represented by composite indicators that explain the main steps to achieve food sustainability: basic needs coverage, production and distribution variety, quality and nutrition, sustainable mechanisms. The OECD methodological recommendations (OECD, 2008) were followed in the development of each index.

Researchers had looked closely at measuring food and nutrition security in the short term to address the risks countries face due to crises, conflicts or other unforeseen shortages in food supply. Several indicators have been developed for this purpose, all using different methodologies and approaches (Pangaribowo et al., 2013). The one that comes closest to our measurement is the Global Food Security Index (The Economist, 2021), which brings together more than 25 indicators describing four categories: affordability, availability, quality and safety, natural resources, and resilience. A major concern regarding this existing index relies on the lack of granularity when it comes to developing strategies for different countries. In many cases, international organisations may recommend food sustainability regulations to governments that have not even managed to achieve sufficient food supply for their populations. In this case, such guidelines may have to wait until the country in question is able to meet the basic requirements of the previous policies and targets. Due to the vague definition of the concept of food security, most of the currently proposed indicators represent unclear snapshots of the status in this area. Moreover, the limitations of a composite indicator in terms of data quality will increase hesitation among decision-makers (Santeramo, 2014).

To avoid this inconvenience, we explored the possibility of creating three linked composite indicators at different levels to ensure efficient allocation of resources and policies. This approach has proven successful in other areas, such as finance, through the Equity and Fixed Income Country Classification (FTSE Russell, 2021), where markets are classified at different levels allow the investors to easily evaluate them. That is, the first level should measure the ability of a country to produce and procure the amount of food necessary for the survival of its population. In other words, the country should be able to secure its food supply or, if this is not fully possible, have easy access to the external market. The second level is defined to ensure food diversity when it comes to producers, traders, imports, infrastructure, access to information and entrepreneurship, and people's choices and behaviour when it comes to quality, nutritional information, and lifestyle. The highest level will point to the environmental impacts of the food industry, as well as research and development. In this way, we will reduce the biases that are most likely to be present in a measurement that combines indicators in all different areas, and we will also facilitate the understanding process to quickly take the specific relevant actions in all situations.

Now, the consequences of the economic instability caused by the pandemic COVID-19 are being felt. Food security has been severely affected by the restriction and pressure on the supply of goods, as well as high unemployment and shortages in the national budget. The current review will also serve as a reminder to decision-makers to gradually rethink their food and nutrition commitments by prioritising the most critical constraints at different levels of activity.

2. LITERATURE REVIEW

Over the past decades, several definitions of food security have been agreed upon by global institutions. Starting with the link to production and supply and ending with a multidimensional approach (Napoli et al., 2011), the concept has encompassed four pillars: availability, access, use and stability. In this way, several composite indicators have been proposed, as presented in Table 1.

Table 1. Existing food indicators (Source: authors' findings)

Indicator	**Reference**	**Covered areas**
Prevalence of undernourishment (POU)	FAO, 2021	Nutrition
The Global Hunger Index (GHI)	Concern Worldwide and Welthungerhilfe, 2020	Nutrition
Dietary Diversity Score (DDS)	Habte and Krawinkel, 2016	Nutrition
Hunger and Nutrition Commitment Index (HANCI)	Lintelo et al., 2014	Nutrition
The Poverty and Hunger Index (PHI)	Gentilini and Webb, 2008	Nutrition
Prevalence of moderate or severe food insecurity	FAO, 2021	Accessibility
The Global Food Security Index (GFSI)	The Economist, 2021	Affordability, availability, quality, resilience
The Proteus Composite Index	Caccavale and Giuffrida, 2020	Availability, access, utilization, stability
Proportion of agricultural area under productive and sustainable agriculture	FAO, 2021	Sustainability
Food Sustainability Index (FSI)	The Economist, 2018	Sustainability
Food system sustainability indicator	Bene et al., 2019	Sustainability
The European Food Regulatory Environment Index	Lima et al., 2021	Nutrition policies

Eco-efficiency indicators for food consumption	Abdella et al., 2021	Sustainability

The relatively high number of existing indicators proves the lack of consensus on the most representative indicator to measure the capacity of the nutrition sector. Most of them address the nutrition issues in close relation with poverty and demographic proxies (Gentilini and Webb, 2008; Habte and Krawinkel; 2016; Lintelo et al., 2013), while the others follow the 4-pillar approach in monitoring the food security (FAO, 2021; The Economist, 2021; Caccavale and Giuffrida, 2020). Therefore, after 1996, the socio-economic perspective has gained many supporters, and extensive research has been conducted, resulting in uncoordinated work and overlapping views (Pagaribowo, 2013). The sustainability area of the topic is still evolving, with international agencies committed to delivering trustworthy results by 2030 (FAO, 2021). As a common pattern, most of the authors are leaning towards the same metrics when analysing the food sustainability: nutrient adequacy, affordability, availability, wellbeing, resilience, safety and waste reduction (Chaudhary and Brooks, 2018) which can be further grouped into the social, economic and environmental aspects of the concept (Bene et al., 2019).

The closest approach to ours is given by the Global Food Security Index (The Economist, 2021), which incorporates the most important aspects of food security, including the ecological footprint. It simultaneously highlights the most critical issues that can weaken the world's stability and deepen the food crisis. In other words, the focus is on rising food prices, access to finance in agriculture, dependence on food aid, volatility of supply, and nutrition strategies and greening of processes.

An important aspect of a consistent food system indicator was highlighted by International Food Policy Research Institute (2015) and it is represented by a dynamic supply and demand process influenced by the people's choices at every stage, from farm to flush. It proposes at the same time a set of five features to guide stakeholders toward improvements in the food systems. The first one defines the agricultural productivity per worker as a sectoral efficiency and quantity assessment. The second one features the supply diversity developed by consumption choices and available nutrients for the population, whereas the other three reflects the accessibility, natural resource availability and demographics as determinants of the food demand and requirements.

Research on food security has broadened the perspective on this area and laid the foundations for other concepts that are gaining interest in these times. One of these is addressed as part of our set of indicators, namely food sustainability.

Our approach follows a similar pattern to the other indicators described earlier, but with two important changes. The first is in the way the pillars are conceptualised and calculated. Previously, monitoring was based on availability, access, use, stability, and their variations. The current process considers a simpler method to make policy development more efficient, monitoring first and foremost whether basic needs are met, then further people's choices when it comes to food and economy, and finally, the ability of countries to replace their less environmentally friendly processes with new and sustainable ones. This approach is driven by an eliminatory mechanism, where low-performing countries cannot move forward and have no way to implement the next category of measures if the first ones do not deliver consistent results. The second change is in the way the variables are grouped. In each of the new layers, there will be variables from all the existing pillars from similar research.

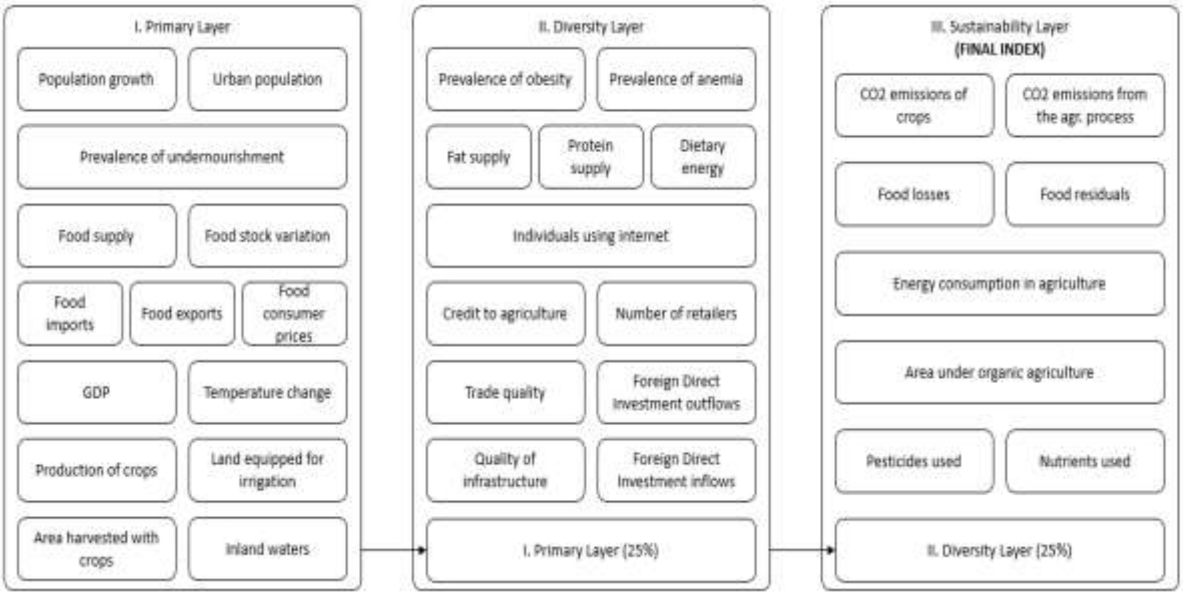

Figure 1. The 3-levels approach structure (Source: authors' computation)

Figure 1 shows all the variables included in each of the main pillars, with the previous layer counting for 25% of the new level.

1.1 Primary layer

The main purpose of the first indicator is to assess and monitor the basic needs of a country and its population in terms of food availability and access. The main logic behind the selection of sub-indicators lies in the behaviour of a human being. At a micro level, to survive, a person needs to procure food by growing it or buying it from others. At the same time, the surplus can then be sold to others in need. To achieve this, the person needs an income, land and water for cultivation, and stable conditions. Translated to the macro level, a country counts on its gross domestic product as a source of income (Coates et al., 2003; Barrett, 2010; The Economist, 2021), its land area that can be used for agriculture, inland waters, environmental conditions to assess risks, imports and exports, political stability, and demographic measures (Haysom and Tawodzera, 2018). The indicators included in this layer are reflected in Table 2.

Table 2. Variables included in the first composite indicator (Source: authors' findings)

Code	Description	Unit	Year	Source	Obs.	N/A[a]	Polarity
GDP	Gross domestic product per capita, PPP	ct. 2011 int. $	2019	FAO	180	4%	+
Crops_prod	Total production of crops	tons	2019	FAO	188	0%	+
Harvest_area	Area harvested with crops	% of total area	2019	FAO	188	0%	+
Waters	Inland waters	% of total area	2018	FAO	153	19%	+
Irrigation	Land area equipped for irrigation	% of total area	2018	FAO	172	9%	+
Temp_change	Temperature change on a meteorological year	°C	2019	FAO	185	2%	-
Prices	Food consumer Prices	Index	2019, Jan.	FAO	176	6%	-

Imports	Total food import quantity	1000 tons	2018	FAO	167	11%	-
Exports	Total food export quantity	1000 tons	2018	FAO	167	11%	+
Supply	Food supply	kcal/capita /day	2018	FAO	167	11%	+
Stock_variation	Total food stock variation	1000 tons	2018	FAO	167	11%	-
Stability	Political stability and absence of violence/terrorism	Index	2018	FAO	188	0%	+
Undernourish.	Prevalence of undernourishment	% (3-year average)	2017-2019	FAO	188	0%	-
Pop_growth	Population growth	%	2019	World Bank	188	0%	+
Urban	Urban population	%	2019	World Bank	188	0%	+

NOTE: a. Percentage of missing values

1.2 Diversity layer

The horizon widens as we introduce the concepts of consumer and market in the first logic. Therefore, the second part will monitor economic flows, agricultural development (Odening and Huttel, 2021) and the availability of food diversity, as well as consumers reservations and whims when choosing products (Maxwell et al., 2013). The second indicator will refer to the countries of the first indicator that have exceeded a set threshold and its values as part of a new sub-indicator that will be added to the following ones in Table 3.

Table 3. Variables included in the second composite indicator (Source: authors' findings)

Code	**Description**	**Unit**	**Year**	**Source**	**Obs.**	**N/A**	**Polarity**
FDI_inflows	Foreign Direct Investment inflows	million US$	2019	FAO	185	2%	+
FDI_outflows	Foreign Direct Investment outflows	million US$	2019	FAO	163	13%	+
Infra	Quality of overall infrastructure	Index	2017-2018	Global Competitiveness Index	149	21%	+
Trade_quality	Quality of trade and transport	Index	2018	World Bank	166	12%	+
Credit	Credit to agriculture, forestry, and fishing	% of total credit in US$	2019	FAO	123	35%	+
Retail	Number of retailers in the food industry	Number	2021	Retail index	77	59%	+
Internet	Individuals using the Internet	% of total population	2019	World Bank	188	0%	+
Fat_supply	Fat supply quantity	g/capita/day	2018	FAO	167	11%	+
Protein_supply	Protein supply quantity	g/capita/day	2018	FAO	167	11%	+

Dietary	Average dietary energy supply adequacy	% (3-year average)	2017-2019	FAO	172	9%	+
Obesity	Prevalence of obesity in the adult population (18 years and older)	%	2016	FAO	186	1%	-
Anemia	Prevalence of anaemia among women of reproductive age (15-49 years)	%	2016	FAO	184	2%	-

1.3 Environmental layer

Under the current movement to reduce industry pressure on the environment, the last indicator strongly promotes a sustainable approach to food production and consumption by monitoring the factors that may increase or decrease the rate of achieving sustainability goals (Table 4).

Table 4. Variables included in the third composite indicator (Source: authors' findings)

Code	Description	Unit	Year	Source	Obs.	N/A	Polarity
Pesticides	Total pesticides used	tons	2018	FAO	159	15%	-
Nutrients	Total nutrients used	tons	2018	FAO	161	14%	+
Organic	Area under organic agriculture	% of total area	2018	FAO	159	15%	+
Energy_use	Energy consumption in agriculture	Terajoule	2018	FAO	156	17%	-
Food_loss	Food losses	1000 tons	2018	FAO	167	11%	-
Food_resid	Food residuals	1000 tons	2018	FAO	167	11%	-
Crop_emissions	CO2 emissions intensities of crops	gigagrams	2017	FAO	187	1%	-
Process_emissions	CO2 emissions produced in the different agricultural sub-domains	gigagrams	2018	FAO	188	0%	-

Therefore, the final step is to monitor the quality of agricultural production using less polluting resources, the footprint on the environment and the measures to further develop processes with sustainable approaches (UN, 2021).

3. METHODS

The building process of a composite indicator can face several challenges. First, the incentive to approach this method is compromised by the unavailability of desired individual indicators, their low quality or missing values for some states or years. The impact of these inconveniences can be mitigated by using proxy data with similar behaviour. Secondly, it is considered to have a high degree of subjectivity. In this way, Caccavale (2020) mentioned conducting the uncertainty analysis to test the output variability when choosing different methods and sensitivity analysis to determine the differences in scores between units. To limit concerns about the quality of the index output quality, we follow the OECD manual for constructing an index for each of the intended indicators.

3.1 Theoretical framework

From a holistic perspective, the current research will focus on measuring food availability, diversity and sustainability. Using this approach, we will describe a state's ability to balance its food supply and demand, the diversity of commodities, producers and distributors, and the quality of infrastructure. In addition, the agribusiness footprint on the environment will be captured in the third measure.

3.2 Data selection

A good practise underlined by numerous researchers is to carefully select the underlying variables of the composite indicator to ensure its high quality and reduce its weaknesses. Our approach was to select the most appropriate indicators for each of the phenomena analysed. The main challenge was to find readings available for all the UN-recognised countries and a temporal dimension close to the current date. Proxy variables were considered in case many values were missing. For each of the scenarios considered, the target number of output variables used for the analysis was set between 5 and 15. Several data sources were used: Food and Agriculture Organisation of the United Nations Database FAOSTAT, The World Bank Database DataBank, World Trade Organisation Database, Organisation for Economic Co-operation and Development STAN Database, Eurostat.

3.3 Missing values

To fill in the missing values in all variables, different techniques were used. They were first taken individually and treated on the basis of specific behaviour. In the cases where only a few values were missing, the approach was to check the previous years. In the situation where a large number of values were missing, K-nearest neighbours were used for data entry. The assumption behind the algorithm is that a value can be approximated by using the nearest points. According to Richman (2011), the technique relies on the assumption that similar observations are expected to produce similar results. A a new observation is created with a predicted value, based on the mean of its nearest neighbour in the preprocessed set. For the computation, we use the R package "caret" to create the k-NN algorithm. The first step was to create the training, which is further used in the preProcess function to input the missing values. By default, the values are normalised. To get the original values, the process will follow the standard approach of multiplying the values by the standard deviation and adding the average. Another way to input the missing values was Amelia II, an algorithm that uses bootstrapping and maximization methods to calculate the missing values (Honaker et al., 2011).

3.4 Correlation, factor analysis and normalization

The next step in our analysis is determined by the behaviour of the variables in relation to each other and the transformations necessary to be comparable. Correlation is measured by the Pearson coefficient. Normalisation is required before the next method, as it reduces the differences between the indicators. Two methods were initially used to normalise the values, min-max and z-scores. We were inclined to use min-max as it fits all values in the range [0, 1]. But given the relatively high number of outliers, the resulting values tended to be closer to the extremes, making it difficult to distinguish the final scores for the countries as most reached the maximum value of 1. This inconvenience forced us to use z-scores to obtain a distinguishable difference between individuals. For the resulting uncorrelated indicators, factor analysis is further applied to explore the structure of the data and how different variables change. Principal component analysis reduces the standardised data from large data sets into a smaller one to facilitate exploratory analysis while retaining most of the information from the original data set (Jolliffe et al., 2016). The method calculates the covariance matrix to explore the correlation between variables, and the eigenvectors and eigenvalues to identify the main factors and group the indicators accordingly. On the other hand, factor analysis will focus more on examining the factors responsible for the observed phenomena. A similar approach is used as described above for principal component analysis, with some differences. First, FA assumes that measured performance is based on the underlying factors, whereas principal components are based directly on the measured performance. Second, in FA, the variance can be divided by the frequency of the factors, resulting in a principal component for common factors, and another principal component for unique factors (Nardo et al., 2005; El Gibari et al., 2019). The principal components will contain both common and unique variance, as they are defined as linear combinations of measurements. PCA is therefore used by factor analysis as a method to group the variables into unrelated factors (Balasundaram, 2009; Watkins, 2018) and extract them. On the other hand, the most important part of this analysis for our research is the factor rotation to maximise the loading of each variable on one of the extracted components while minimising the loading on all other components. The method we chose was the varimax approach to make it as easy as possible to calculate the weights of each country in our dataset. A simple way to understand factor analysis was described by Norusis (1993) and revisited by Howard (2016). The process starts with the correlation matrix between all the variables and then proceeds to factor extraction using principal component analysis, where linear combinations of variables are calculated. Factor coefficients or loadings are then calculated to map the variables to their factors. The resulting factor models are rotated to prevent the presence of zero values, but also to make the matrix more understandable. The resulting scores are used for further analysis.

3.5 Weighting and aggregation

Factor analysis plays an important role in this step, as it is the starting point for calculating the weights for each indicator, as well as for each country in the dataset (Gomez-Limon et al., 2003; Odu, 2019). The factor loadings after rotation are squared, and the maximum value for each of the variables is then used to calculate the weights. The final score is determined using the "Benefit of the Doubt" method (Cherchye et al., 2007; Rogge, 2018) by dividing the sum of the multiplication of the normalised value and the respective weights by the same formula for the individual that maximises the values for each of the variables called benchmark performance, as in the formula below:

$$\text{Equation 1: } CI_c = \frac{\sum_{c=1}^{M} I_{qc} w_{qc}}{\sum_{c=1}^{M} I_{qc}^{*} w_{qc}}$$

where Iqc is the normalized value of qth variable (q=1,…,Q) for country c (c=1,…,M) and wqc the corresponding weight. Arithmetic aggregation was used in determining the final scores of all three layers, as it is commonly used in the formation of composite indicators (Otoiu and Gradinaru, 2018).

4. RESULTS

4.1 Composite indicators calculation

In most cases, the summary statistics show a skewed distribution, determined by the outliers. China is by far the country that shows the largest differences from the others, as is Venezuela in food prices, due to the current political situation.

Looking at the three layers, the correlation coefficients show a relatively low correlation between the variables, with some exceptions. GDP and urban population can both be considered as factors of wealth, proving that the trend is proportional. Stock variation can be influenced by the outcome of crop production if it is not constant, and by inflows and outflows. The country's food reserve can directly increase the prevalence of malnutrition.

For the second indicator, we can see that the supply of nutrients is presented as highly correlated due to their common magnitude. The correlation with internet use, on the other hand, may be pure coincidence or evidence that people frequently use internet resources when it comes to their nutritional decisions. The number of retailers in a state is certainly related to foreign direct investment in a country.

For the third layer, most variables are highly correlated, as a large amount of an additive used in agriculture produces higher amounts of CO2 emissions. The same logic applies to energy use. We have chosen not to eliminate the correlated variables to ensure that countries that use polluting mechanisms and damage more than one different part of the environment (in our case both soil and air), are include in the calculation at least twice. On the other hand, efficient measures to reduce the ecological footprint will determine a much higher change in the ranking.

Looking further into data suitability, we need to see if the available indicators fit the phenomenon described and thus keep the composite indicator balanced. Factor analysis is used to investigate the relationship behaviour between variables and to group the information (Figure 2).

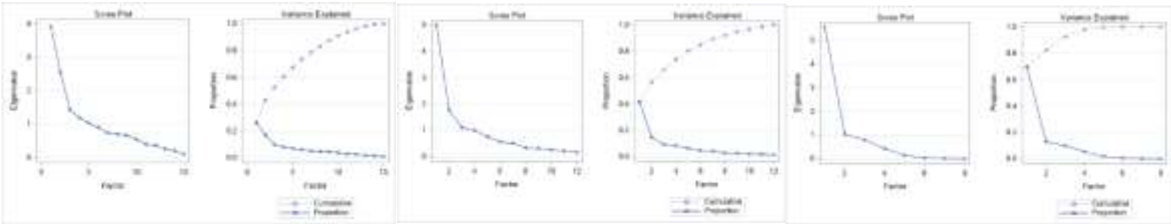

Figure 2. Recommended number of factors in each case (Source: authors' computation using SAS)

For all indicators, four factors were retained after calculation to facilitate comparability among them, and the individual variables were grouped accordingly. The resulting rotated matrix shows in each case the factors that were considered for weighting and the resulting weights of the variables.

Table 5. Rotated matrix and weights of the squared factor loadings for primary layer (Source: authors' computation)

Variable	**Rotated factor pattern**				**Weights of the factor loadings**				**Variables weights**
	F1	F2	F3	F4	F1	F2	F3	F4	
GDP	0.82	0.16	-0.17	0.01	0.19	0.01	0.02	0.00	9%
Crop_prod	-0.08	0.80	0.19	-0.03	0.00	0.23	0.02	0.00	8%
Harvest_area	-0.18	0.03	0.80	0.06	0.01	0.00	0.40	0.00	9%
Waters	-0.02	0.03	0.25	0.22	0.00	0.00	0.05	0.04	1%
Irrigation	0.03	0.15	0.75	-0.03	0.00	0.01	0.35	0.00	8%
Temp_change	-0.49	0.21	-0.10	0.19	0.07	0.02	0.01	0.03	3%
Prices	0.13	-0.02	0.09	0.86	0.00	0.00	0.01	0.62	10%
Imports	-0.27	-0.72	-0.04	0.01	0.02	0.18	0.00	0.00	6%
Exports	0.21	0.86	-0.05	0.03	0.01	0.26	0.00	0.00	9%
Supply	0.83	0.26	-0.01	0.09	0.20	0.02	0.00	0.01	9%
Stock_variation	0.06	-0.84	-0.10	-0.03	0.00	0.25	0.01	0.00	8%
Stability	0.66	-0.10	-0.12	0.12	0.13	0.00	0.01	0.01	6%
Undernourishment	0.67	0.13	0.05	0.29	0.13	0.01	0.00	0.07	6%
Pop_growth	-0.60	-0.05	-0.36	0.46	0.10	0.00	0.08	0.17	3%
Urban	0.67	0.22	-0.30	-0.22	0.13	0.02	0.06	0.04	6%

In the first case, the price of food accounts for 10% of the total indicator and thus proves to be the most influential factor. We cannot say the same about inland waters, whose values will not make much difference. Consequently, the worst performing countries need to focus more on fiscal and economic policies to stabilise inflation.

Table 6. Rotated matrix and weights of the squared factor loadings for diversity layer (Source: authors' computation)

Variable	**Rotated factor pattern**				**Weights of the factor loadings**				**Variables weights**
	F1	F2	F3	F4	F1	F2	F3	F4	
CI1									25%
FDI_inflows	0.09	0.17	0.87	-0.08	0.00	0.01	0.39	0.01	9%
FDI_outflows	0.61	-0.41	0.38	0.19	0.11	0.07	0.07	0.04	4%
Infra	0.79	0.10	0.12	-0.21	0.19	0.00	0.01	0.04	6%
Trade_quality	0.79	0.19	0.37	-0.07	0.19	0.01	0.07	0.00	6%
Credit	-0.10	-0.01	-0.03	0.97	0.00	0.00	0.00	0.89	9%

Retail	0.23	0.01	0.86	0.04	0.02	0.00	0.38	0.00	9%
Internet	0.74	0.46	-0.02	-0.04	0.16	0.08	0.00	0.00	6%
Fat_supply	0.60	0.64	0.22	-0.01	0.11	0.16	0.02	0.00	5%
Protein_supply	0.55	0.65	0.15	0.00	0.09	0.16	0.01	0.00	5%
Dietary	0.20	0.71	0.27	0.08	0.01	0.20	0.04	0.01	6%
Obesity	-0.05	-0.76	0.09	0.09	0.00	0.23	0.00	0.01	6%
Anemia	0.59	0.45	0.06	0.06	0.11	0.08	0.00	0.00	4%

The second layer is not much different from the first, as the most addressed area is also economic and financial. The most common strategy is to promote a free market, open to international investment, as the inflow of foreign direct investment and the number of retailers account for 18% of the total indicator. At the same time, supporting the activities of local farmers will significantly increase the country's performance (Kuckertz et al., 2019).

Table 7. Rotated matrix and weights of the squared factor loadings for sustainability layer (Source: authors' computation)

Variable	**Rotated factor pattern**				**Weights of the factor loadings**				**Variables weights**
	F1	F2	F3	F4	F1	F2	F3	F4	
CI2									25%
Pesticides	0.47	0.85	-0.16	0.02	0.06	0.37	0.02	0.00	11%
Nutrients	-0.77	-0.60	0.17	-0.04	0.16	0.18	0.03	0.00	8%
Organic	0.06	0.03	0.03	1.00	0.00	0.00	0.00	0.99	10%
Energy_use	0.63	0.72	-0.17	0.05	0.11	0.26	0.03	0.00	8%
Food_loss	0.87	0.37	-0.14	0.07	0.20	0.07	0.02	0.01	8%
Food_resid	-0.17	-0.15	0.97	0.03	0.01	0.01	0.87	0.00	10%
Crop_emissions	0.93	0.33	-0.14	0.04	0.23	0.05	0.02	0.00	10%
Process_emissions	0.94	0.30	-0.14	0.04	0.23	0.05	0.02	0.00	10%

The focus for the last step would be to reduce the use of chemical treatments applied to the soil, as they affect most of the other variables proportionally.

An important aspect to be pointed out again is the number of observations considered after each calculation. In the first stratum, 176 out of 194 countries are analysed because Comoros, Equatorial Guinea, Eritrea, Libya, Marshall Islands, Micronesia (Federated States of), Nauru, Qatar, Somalia, South Sudan, Tonga, Tuvalu have too many missing values and imputation would have resulted in wrong values, and the rest of the remaining countries were not even included in the source datasets.

Countries that rank below the first quartile value for the first indicator are removed from the next calculations and advised to improve their food policies as they have not been able to meet the basic needs of the population. Figure 4 shows the ranking for the primary layer. The first places are not a surprise as they perform very well in all areas. The biggest surprise is Bangladesh, which can be explained by its high proportion of irrigated land, stability of food supply and low prices. The "eliminated" countries are mostly from Africa, South America, or conflict-affected areas.

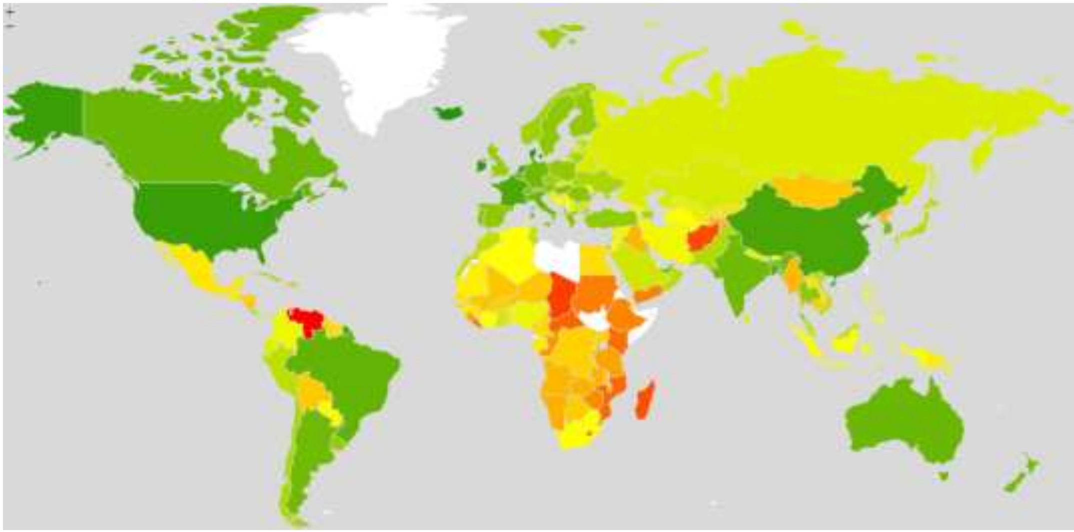

Figure 4. Representation of primary layer results (Source: authors' computation)
Note: Red – low performance; green – high performance; white – no data.

The second level ranking is calculated for 132 states, and the first indicator becomes a sub-indicator with 25% rated importance in the result. Thus, the United States takes the top position due to its highly developed market and infrastructure. Even if a country performs well in a previous stage, it may not reach the requirements of the next level. This is the case of Bangladesh, which has a very low developed market, poor infrastructure and a high prevalence of anaemia among women.

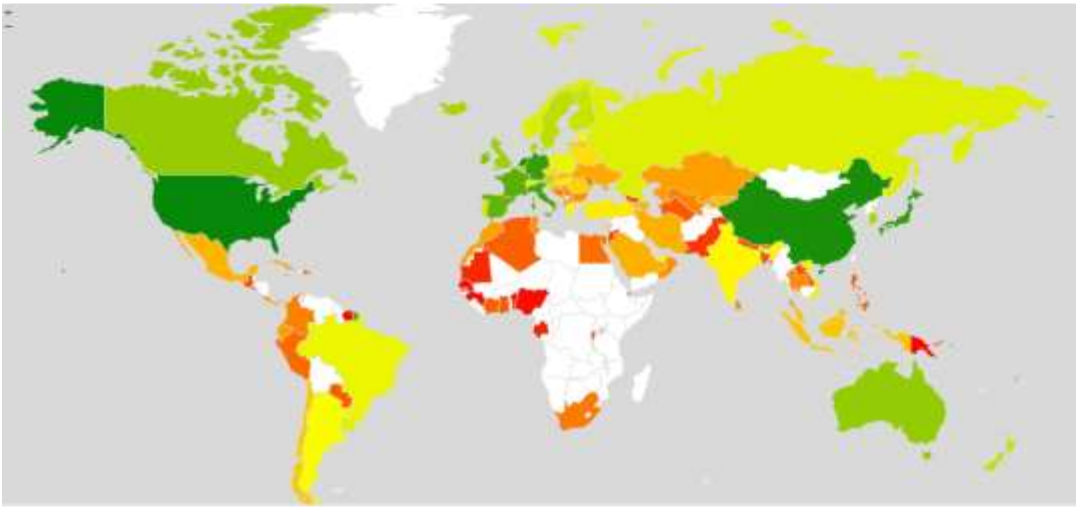

Figure 5. Diversity layer results (Source: authors' computation)

Note: Red – low performance; green – high performance; white – minimum criteria not reached or no data.
The remaining 99 countries are classified in terms of sustainability. As mentioned earlier, countries that scored very well in the previous steps may score low in the next steps due to a different scope of the measure. This is the case for the United States and China, which have difficulties meeting the new sustainability requirements due to their enormous industrial capacity.

Table 8. Sustainability layer scores (Source: authors' computation)

Country	Score	R	Country	Score	R	Country	Score	R	Country	Score	R
Netherlands	0.729	1	Slovakia	0.664	26	Montenegro	0.644	51	Bosnia Herzegovina	0.631	76

Italy	0.717	2	Croatia	0.663	27	Mauritius	0.644	52	Kazakhstan	0.631	77
France	0.715	3	Seychelles	0.661	28	Vietnam	0.644	53	Dominica	0.631	78
Spain	0.713	4	South Korea	0.660	29	Azerbaijan	0.643	54	Samoa	0.631	79
Austria	0.706	5	Israel	0.660	30	UAE	0.643	55	Indonesia	0.630	80
Denmark	0.703	6	Hungary	0.660	31	Trinidad Tobago	0.643	56	Ghana	0.629	81
Germany	0.694	7	Poland	0.659	32	Kyrgyzstan	0.642	57	Djibouti	0.628	82
Ireland	0.692	8	Slovenia	0.659	33	Bulgaria	0.642	58	Bahamas	0.628	83
Belgium	0.686	9	Ecuador	0.657	34	Chile	0.641	59	Egypt	0.627	84
Czechia	0.684	10	Bahrain	0.657	35	Thailand	0.641	60	Peru	0.624	85
Singapore	0.681	11	Ukraine	0.656	36	Armenia	0.641	61	Russia	0.623	86
Estonia	0.680	12	New Zealand	0.656	37	Kiribati	0.640	62	Morocco	0.623	87
Switzerland	0.680	13	Norway	0.655	38	Saudi Arabia	0.640	63	Paraguay	0.621	88
Greece	0.673	14	Uruguay	0.654	39	Sri Lanka	0.639	64	Philippines	0.620	89
Luxembourg	0.672	15	Romania	0.653	40	Serbia	0.639	65	Algeria	0.617	90
Latvia	0.672	16	Tunisia	0.652	41	Bhutan	0.639	66	Colombia	0.617	91
Portugal	0.672	17	Canada	0.651	42	Panama	0.639	67	Iran	0.616	92
Sweden	0.671	18	Malta	0.649	43	St. Kitts and Nevis	0.638	68	Mexico	0.615	93
Lithuania	0.670	19	Malaysia	0.649	44	Albania	0.638	69	Argentina	0.613	94
Brunei	0.669	20	Barbados	0.649	45	Oman	0.637	70	US	0.570	95
Japan	0.667	21	Dominican R.	0.649	46	North Macedonia	0.636	71	Uzbekistan	0.549	96
UK	0.667	22	Costa Rica	0.645	47	Turkey	0.634	72	India	0.473	97
Australia	0.667	23	Kuwait	0.645	48	Ivory Coast	0.633	73	Brazil	0.463	98
Iceland	0.666	24	Belarus	0.644	49	Cuba	0.633	74	China	0.363	99
Finland	0.664	25	Cyprus	0.644	50	South Africa	0.633	75			

4.2 Uncertainty analysis

The subjectivity that occurs at the beginning of the analysis due to the methods chosen has led to the need to perform uncertainty (UA) and sensitivity (SA) analyses. This step prevents the results from being misinterpreted or misleading (Moreira et al., 2021). The sources of uncertainty are present in every step of the construction of the composite indicator, from the selection of variables to the aggregation procedure. Both UA and SA have the same scope but slightly different roles (Saisana et al., 2005; Loucks and van Beek, 2017). The former focuses on how the uncertainty of the sub-indicators propagates through all steps of the index, while SA focuses on the weight with which each source affects the final result.

From a theoretical perspective, the composite indicator can be described as a function of Q normalised indicators for c countries and the weight:

Equation 2: $CI_c = f_{rs}\left(I_{1,c}, I_{2,c}, \dots, I_{Q,c}, w_{s,1}, w_{s,2}, \dots, w_{s,Q}\right)$

where r is the aggregation system and s, the weighting scheme.

The result of the uncertainty analysis is represented by the rank assigned to a country by the composite indicator and the average shift in country rankings (OECD, 2008):

Equation 3: $\overline{R_s} = \frac{1}{M}\sum_{c=1}^{M}\left|Rank_{ref}(CI_c) - Rank(CI_c)\right|$

Several steps in the creation of the composite indicator can lead to uncertainties that affect the assigned ranks. By following the Monte Carlo approach to evaluate the phenomena, several triggers were used to assess the possible cases, as shown in Table 9. Based on these scenarios, several simulations are performed to calculate the differences between the chosen method and all other possibilities.

In our case, all calculated indices deal with 4 sources of uncertainty: variable exclusion, imputation of missing values, normalisation, and weighting. As suggested by Saisana et al. (2005) and reiterated by Caccavale and Giuffrida (2020), uncertainty analysis became a must in the formation of composite indicators because of the doubts raised by the subjectivity in the choice of a method, which can cause both the robustness of the final rankings and reduced significance. Aggregation was not included in the analysis because we are forced to use only arithmetic aggregation due to its simplicity and the absence of assumptions about the relationship between the sub-indicators, which has already been addressed by factor analysis.

Table 9. Assumptions for the sustainability layer (Source: authors' findings)

Input factor	**PDF**	**Method**	**Subjective choice**
Variable exclusion	1	All included	X
	2	Excluded: Pesticide usage	
	3	Excluded: Nutrients used	
	4	Excluded: Energy consumption in agriculture	
	5	Excluded: Food losses	
	6	Excluded: Emissions from crops	
	7	Excluded: Emissions from the agricultural processes	
Data imputation	1	Missing data exclusion	
	2	k-NN	X
Normalization	1	Min-max	
	2	Standardization	X
Weighting	1	Equal weights	
	2	Factor analysis	X

The uncertainty analysis will focus on five scenarios, including all variables, k-nearest neighbour, either min-max or standardisation and equal or FA weights. Taking the last calculated indicator as a reference, we will recreate the scores of all 99 countries and compare between them to see how high discrepancies might have led to the loss of information. Figure 6 shows the last 20 countries ranked by their mean score. We will see that the last 3 countries keep the same rank in all the cases, while the others can vary up to 40 positions. While our assumptions for the last positions seem less optimal than others, the first countries in the ranking indicate the right decision, as the others show anomalies in isolated cases.

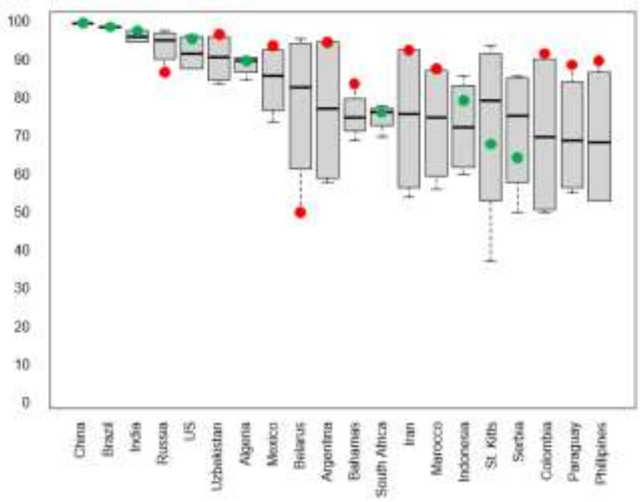

Fig. 6. The score ranges for the last 20 countries in the sustainability layer (Source: authors' computation)
Note: The bullets represent the subjective assumptions; green – optimal score, red – less optimal than the other assumption

By performing the sensitivity analysis for each of the variables for our assumptions, we get very high disturbances caused by one or two measures in all cases. Agricultural energy consumption is by far the indicator that causes the largest deviation from the others, apart from nutrient consumption, arable land for organic farming, food residues and emissions from arable farming.

5. Discussion

The entire analysis was applied three times for each of the designed layers. The variables contain 2019 values, with some exceptions due to unavailability of data or provider assumptions. The first level was calculated for 176 countries after dealing with the missing values. Countries with scores below the threshold represented by the first quartile were eliminated and those remaining were counted for the next level. The diversity layer was built on 132 observations, of which 99 went on for the final level, the sustainability layer. As a summary of the final values, the values of the first indicator ranged from 0.2621 to 0.6158, the interval for the second was [0.3057, 0.6565], while the third indicator had a higher range, namely [0.3633; 0.7285]. Overall, the most efficient country is the Netherlands as the top country in the last tier, which includes a small proportion of the other two. The last country is considered to be in the last position of the first layer, Venezuela. From the "eliminated" states, 52% are from Africa, 24% from Asia, 18% from Central and South America, 3 from Oceania and 1 from Europe. Under the current assumptions, Moldova could not move up to the third level, so the country must reduce the minus points for the areas covered by the diversity layer.
The 3- Step Food Sustainability Indicator was developed as a tool for governments and international institutions to focus on and address the most critical aspects of food security before moving forward with innovative but unachievable ideas. In this way, a country struggling to provide basic needs to its population is guided by sound policy to address these inconveniences first before embarking on the design of sustainability regulations. This is also the most visible difference between our approach and the existing indicators.
Table 10 shows the comparison of the top 20 countries in some of the previously mentioned indicators, for 2019.

Table 10. Comparison between our results and existing indicators (Source: authors' findings)

Rank	PDS – Level 3	GFSI	FSI (2018)	Proteus (2017)
1	The Netherlands	Singapore	France	Belgium
2	Italy	Ireland	The Netherlands	Luxembourg
3	France	United States	Canada	Austria
4	Spain	Switzerland	Finland	Switzerland
5	Austria	Finland	Japan	Germany
6	Denmark	Norway	Denmark	Italy
7	Germany	Sweden	Czechia	France
8	Ireland	Canada	Sweden	Qatar
9	Belgium	The Netherlands	Austria	Ireland
10	Czechia	Austria	Hungary	United Kingdom
11	Singapore	Germany	Australia	Israel
12	Estonia	Australia	Rwanda	Denmark
13	Switzerland	Qatar	Argentina	Czechia
14	Greece	Denmark	Croatia	Spain
15	Luxembourg	Belgium	Poland	The Netherlands
16	Latvia	France	Germany	Malta
17	Portugal	United Kingdom	Colombia	Portugal

18	Sweden	Israel	Ireland	Greece
19	Lithuania	New Zealand	Spain	United States
20	Brunei	Portugal	Estonia	Slovenia

We can see that 85% of the countries in the third layer ranking are in at least one of the published indicators selected in the table. The first country, the Netherlands, appears in all the indicators' top 20, as do Austria, Denmark, Germany and Ireland. The countries highlighted in red appear in at least 2 other indicators, but not in ours. The main reason for this is the main area of the third level, sustainability, as food and economic flows account for 18.75% and basic needs 6.25%. Countries such as the United Kingdom, the United States, Japan, or Canada are known for being the world's largest food exporters, but at the same time the ecological footprint counts just as much, only with a different polarity. A similar approach is found in the Food Sustainability Indicator, where 7 of the top 20 countries are not found in any other food index.

Our approach should not be interpreted as coercion, but as external motivation for policy makers from all over the world. It is worth nothing that a country can be compared to a person on a micro level and tends to behave similarly. Applied to our study, a government will react much more strongly if a clear prize is defined, in this case, a place at the "VIPs" table, than in a so-called "flat ranking" where all countries are part of a single list. Consequently, this motivation should lead to efficient implementation of the food policies in countries that struggle in this action.

If we go into more detail, the primary layer will emphasize the importance of ensuring human health needs and a balanced way of obtaining food. It is strongly related to Maslow's hierarchy and focuses most of its framework on physiological needs: production of food or procurement from external sources, water and living conditions. It also links food regulations to population policies, by relying on the population growth in urban areas where food availability and affordability are always present. The second layer comes with a new perspective and brings market policies, producers, distributors, supply chain and the labour and entrepreneurship. At this point, the recommendation for countries is to focus on inputs and outputs for a healthy economy. At the same time, it monitors the human right to health, information and choice by ensuring the availability of different product ranges and their ingredients and calories. Finally, the sustainability layer promotes current movements in defining and implementing environmentally friendly policies that provide safety and high standards. In summary, our approach achieves all the important points of an efficient food policy, from the basics to the latest trends. Nevertheless, an important advantage of creating a composite indicator in three steps that embeds an elimination system is also that it facilitates the allocation of resources to the most critical areas and levels of food and nutrition (Thomas et al., 2017), namely procurement, market and sustainability.

6. Conclusion

The main assumptions for the newly developed indicators were to increase motivation towards countries to reaffirm their commitment to reduce hunger and streamline the security of food, and to introduce the concept of sustainability and the need for action in states where major changes need to be implemented. This means that our indicator, developed in three steps, can provide solutions to most of the criteria implied by the hypotheses mentioned earlier. Each level focuses on a clear set of guidelines and requirements that a country should follow to achieve food sustainability status. As explained earlier, the first layer will determine whether a state can provide the minimum conditions for its people to live healthy lives and carry out their daily activities, while the second level will oversee the optimal functioning of the economy. The last level in particular will act on the one hand on the sustainable side of food security, but also as an aggregate indicator by considering the results of the other two layers. The countries that have confirmed their strong commitment to the food sector are also highly ranked in our indicators.

In summary, our approach will have an impact on the desire of governments to reaffirm their commitments to protect food security through the motivation that comes from developing an elimination system that can provide a sense of achievement when passed. Furthermore, the results have demonstrated the effectiveness of our third tier in measuring the capacity of countries in this sector, as 85% of the countries in our top 20 are represented in at least one other major food index.

The limitations are mainly determined by the relatively small number of datasets in different topics, such as entrepreneurship in agriculture and food-related market chains, number of enterprises in the respective sectors. Similarly, some important variables could not be used due to their outdated values, such as research and development. The missing data was also a real limitation and forced us to exclude some countries from the analysis or to estimate values for the others. Other limitations were the presence of outliers and the highly correlated factors. From a technical point of view, there is no complete programme or method developed to fully calculate the final rankings. Our analysis was facilitated by various software programmes such as R, SAS, Excel, GIS, and it included both automated methods and manual calculations.

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