On the composite indicators for food security: Decisions matter!

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Abstract

During the past decades, there has been much debate on food security. A variety of indicators have been proposed in order to establish which countriesare in need of improved food security status. The heterogeneity of existing indicators and the lack of consensus on how to compare and rank countries have motivated international organizations to build composite indexes to synthesize the information. The process of building composite indexes involves multiple choices that influence the outcome. Our analysis aims at understanding how relevant and discretional may be the analyst's choice of algorithms to compute composite indexes for food security. To this extent, we have computed several composite indexes for food security by using data provided by the Food and Agricultural Organization, which includes a large set of proxies for food security, as emerged from the Committee on World Food Security Round Table. We compare different methods to impute, homogenize, weight and aggregate data, in order to compute composite indexes and show how relevant are the choices to be made.

We show that normalization and weighting are not very crucial decisions, whereas special attention has to be paid in choosing the data imputation and aggregation methods. By commenting on the implications that different measurement choices may have in terms global index, we show that the index construction decisions matter.

Keywords: Food policy, food security, index, composite index

JEL Codes: C43, O57, O13, Q18

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On the composite indicators for food security: Decisions matter! [1]

"In all things which have a plurality of parts, and which are not a total aggregate but a whole of some sort distinct from the parts, there is some cause."

Aristotle, Metaphysics

1. Introduction

Food security is a major issue in academic and international debates. Its global impact on economic fundamentals has become a focus of concern[19, 37, 43]. Ensuring food security in developing countries is a global goal[23,12]. The Food and Agricultural Organization Director-General's Medium Term Plan 2014-17 and Programme of Work and Budget 2014-15 have redefined the Strategic Objectives (SOs) expected to be achieved over a long-term timeframe by members based on the Food and Agricultural Organization's (FAO) value-added interventions[2]. The first FAO SO is to eradicate hunger, food insecurity and malnutrition[14].

Despite the relevance that food security is gaining over the years, several aspects remain under-investigated. More importantly, the concept itself of food security is elusive due to vague and excessively broad definitions.Numerous indicators for food security have been proposed[7-8, 11, 18-19, 21-22, 26, 32, 29, 42], but it is unclear if "these different constructs equally represent the different domains of food security[25]." Indeed, different indicators may convey different information on food security and should not be considered equivalent[1, 3, 6-7]. Pinstrup-Andersen[38] suggested that "monitoring of food security should be [further] complemented by anthropometric measurements"; Masset[30] argued that correlations among variables, double counting and the

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[2] More information on the Medium Term Plan is available at: http://www.fao.org/docrep/meeting/027/mf490e.pdf

quality of data are major limitations in composite indicators; De Muro and Aurino[(9)] named loss of information and lack of transparency as major limitations of composite indicators. Finally, the methodology to compute food security indicators is not always straightforward.

As pointed during the December 2012 FAO and World Food Programme meeting, “a need has emerged to both systematize and harmonize the way progress can be measured and monitored” in order to expand the coverage of existing information[(31)] and to improve evidence-based decision-making processes. For instance, the FAO aims at widening the evidence baseby proposing novel metrics to assess the evolution and achievement of SOs[3]. In order to be more transparent and objective while monitoring and evaluating the achievement of SOs, the FAOaims at proposing a newcomposite index for evidence-based learning. Several composite indicators are already in use: the Global Food Security Index (GFSI), the Global Hunger Index (GHI) and the Poverty and Hunger Index (PHI) are emblematic examples[(35)].

The process of building a composite index is challenged in many ways: First, the existing evaluations of previous strategic objectives have been misguided by “indicators that were not systematically SMART [Specific, Measurable, Achievable, Relevant and Time-bound] and were often focusing on outputs and activities” [(13)].Second, the composite index approach is inherently threatened by the low quality of indicators, often not available in less-developed countries, the infeasibility of desired indicators, the need of harmonization of standards and frameworks. The entire process should “enhance capacities of data users to use information more effectively, and how data are used could even be monitored in order to justify enhancements and to allow for better prioritization. A continuous and joint assessment of data needs, as well as of existing available data, is essential in order to identify gaps and agree on actions to address them”[(15)]. The

[3] More information on the new metrics that measure food security is available at: http://www.fao.org/fileadmin/templates/ess/global_strategy/GS_High_Level_Meeting/GS2012_EM4_Scorecards_20121204.pdf

above picture clarifies the challenges for the near future. Constructing a unified framework for food security composite indexes is the first, yet crucial, step to be achieved.

We provide a comparative analysis of different composite indexes, based on a range of selected methodologies[34-35]. In particular, we go into depth on different methods for data imputation and several techniques to homogenize, weight and aggregate primary data. Our quantitative comparison is intended to guide experts in selecting the proceduresto build composite food security indicators. Empirical and policy implications are provided.

The remainder of the paper explores theoretical aspects of rank-based indicators, presenting the results of our comparative analysis in section 3; conclusive remarks and implications for future researches are provided in the last section.

2. A toolkit to build food security composite indicators

Indicators to measure food security have been proposed over decades: from narrow measurement on specific variables (e.g., percent of undernourished children, proportion of children who are underweight etc.) to complex indexes aimed at synthesizing the multiple dimensions that characterize food security (e.g., Global Food Security Index, Global Hunger Index etc.). Several classifications have been adopted to organize the indicators. First, indicators of food security may synthesize information at different levels (global, national, household and/or individual); second, indicators may be oriented to one or more dimension of the food security (availability, access, utilization and stability); third, they can be distinguished in static and dynamic indicators (the former take into account only current statistics; the latter summarize time-varying statistics); fourth, they may privilege a particular type of information (proxies associated with the status of food security, with the processes or interventions implemented to target food security or with the determinants or sources of risks associated with food security).

The indicators should be constructed in such a way that they satisfy a range of desirable properties. They should be based on weak assumption, in that the stronger the assumptions, the weaker the credibility of the indicators[(28)]; they should rely on solid conceptual and theoretical frameworks; indicators should be rapidly available and easy to be interpreted. Moreover, indicators should be robust to changes in parameters as well as to measurement errors and have a right balance of stability and sensitivity[(36)]. Institutions should also be aware that the costs to collect information might be a critical aspect. Chambers[(5)] suggested to collect only data strictly needed (optimal ignorance) and to measure the phenomenon at the required level of precision (appropriate imprecision).

A further challenge is how to synthesize information into a single (composite) index. In general, constructing a composite index involves several steps, from the definition of the phenomenon and the selection of information to the imputation of missing information, the homogenization and the aggregation of original indicators into a single index. We review the steps in more detail.

The starting point of any composite indicator has to be the definition of the phenomenon under investigation, and that we aim at measuring. Food security indexes are usually founded on the definition that food and nutrition security exists when all people at all times have physical, social and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life[(4)] [4].

In order to capture the complexity of the phenomenon under analysis, it is important that subgroups (or dimensions) convey different (and possibly unrelated) information. In other terms, the subindexes should be (statistically) independent of each other. Such a nested structure improves the user's understanding of the driving forces behind the composite indicator. It may

[4] More information on the Committee on World Food Security's final report can be found at: ftp://ftp.fao.org/docrep/fao/meeting/018/k7197e.pdf.

also make it easier to determine the relative weights across different factors. This step, as well as the next, should involve experts and stakeholders as much as possible, in order to take into account multiple viewpoints and to increase the robustness of the conceptual framework and set of indicators.

The selection of variables is the second step. Relying on variables of good quality is a major issue for constructing composite indexes. Ideally, variables should be SMART: specific, measurable, accessible, relevant, and timely[(15)]. The data selection process is somewhat subjective. It usually involves a set of heterogeneous indicators: quantitative (hard) data, qualitative (soft) data collected from surveys or policy reviews and proxies aimed at conveying more information on the phenomenon when specific variables are unavailable. The quality and accuracy of the composite indexes crucially depend on available data and their quality.

The third step consists of imputing missing data. Almost all classic and modern statistical techniques assume (or require) complete data, and the vast majority ofexisting statistical packages default to the least desirable option for dealing with missing data: deletion of the case from the analysis. However, deleting observations is always a loss of information that will affect subsequent analyses and inferences on data[(40)]. More information on strategies to handle missing data is available at: http://hdl.handle.net/10179/4355. Quoting Dempster and Rubin[(10)], the imputation of missing data is one of the most critical steps: "It can lull the user into the pleasurable state of believing that the data are complete after all, [but] it is dangerous because [if not applied correctly] estimators applied to real and imputed data [may] have substantial bias." The procedures for missing data imputation can be divided into two categories[(34)]: single and multiple imputations. Single imputation methods are easy to handle, but they systematically underestimate the variance of the estimates. For instance, mean imputation distorts relationships between variables by "pulling" estimates of the correlation toward zero[(35)]. As a rule of thumb, simple methods are preferred if a variable contains less than 5% missing values[27]; otherwise, other (more complex) approaches should be adopted to impute missing data, in that they use more information that would be ignored in case of deletion or single imputation.

The normalization of indicators, the fourth step, can be pursued in several ways[17, 24]. Ranking observations on their relative performance for the selected indicator is the simplest method, although it is not appropriate for complex indicators, in that a large part of information would be loss. Several alternatives are possible (indicator function, relative distance, rescaling etc.), although each of these techniques may be largely biased by outliers. An interesting alternative is to construct a score function for each indicator that isa mapping from the indicator domain in percentile terms to an ad hoc step function. Intervals in a score function can be numeric or categorical. Analogously to other methods based on relative performance (e.g., ranking), part of the information would be lost during the transformation process. A better method is to standardize data (or compute z-scores). It consists of normalizing the indicators to a common scale,imposing the first two moments respectively equal to zero and one. By collapsing all information to a common scale, the empirical distribution of the data is preserved.

A number of weighting techniques exist, none of which is exempt by a discretionary choice[40]. The most common weighting techniques are derived from statistical models (e.g., unobserved components models) or from participatory methods (e.g., budget allocation, analytic hierarchy processes or conjoint analysis). The choice has to be guided by the theoretical framework underlying the scorecard. For instance, equal weighting implies that indicators (or dimensions) have similar importance. The principal components analysis, or factor analysis, relies on data variability and variables correlation: It aims at explaining the highest variation in the data set using the smallest possible number of (aggregated) factors. No need to say, a necessary condition to apply those methods is that variables must be correlated, and correlation can be estimated. Equal weighting (EW) is the most common approach for composite indicators and scorecards[34]; however, equal weights are not synonymous with “no weights” or “fair weights”. The method implies that all variables have the same importance in the composite index, a very weak assumption. Moreover, EW may induce double-counting bias in hierarchical indexes: The more numerous a subgroup of variables, the higher the weight of the subgroup. Therefore, EW may be assumed when theoretical knowledge or empirical evidence are lacking.

The most common approaches to aggregate indicators and dimensions are the linear aggregation and the geometric aggregation[34]. If linear or geometric aggregations are adopted, weights will reflect trade-offs between indicators. The rational can be examined, borrowing the intuition from the economic theory. In general, the high values of some indicators (or dimensions) compensate for low values of the other indicators (or dimensions), but the degree of substitutability is imposed by the assumed functional form. Adopting linear aggregation indicators (or dimensions) will be*perfect substitutes*[29]. On the other hand, the degree of substitutability in geometric aggregation depends on the ratio of the exponents and the level of indicators. A ratio equal to the unity implies an equal contribution of the indicators (or dimensions) to the composite index. Therefore, the difference between linear and geometric aggregation is substantial, and particular attention has to be paid. The compensability is constant in linear models; under a geometric formula, the lower the values of the composite indicators, the lower the compensability.

Let us clarify with an example. If a geometric aggregation is adopted, countries with low scores on one indicator would need a much higher score on the others to improve their ranking. In this case, an efficient strategy to improve the ranking position would be to improve sectors related to the lowest scores. The opposite is true if a linear aggregation is adopted[33].

A more general aggregation formula is the constant elasticity of substitution function that nests linear and geometric aggregation[5].

The following section clarifies how relevant are the choices underlying the process of building a composite index.

3. The theory in practice

We have computed several composite indexes for food security by using data provided by the FAO[6]. The dataset "FAO Food Security Indicators" is constructed by following the recommendation of experts gathered in the Committee on World Food Security Round Table on hunger measurement, hosted at FAO headquarters in September 2011.

The choice of indicators has been mostly informed by data availability with sufficient coverage to enable meaningful comparisons across regions and over the years. The quality and the coverage of available data, as well as the methods through which the relevant information is conveyed, are main constraints to be considered(2). The database introduces a number of new indicators to fill some of the recognized gaps in food security information systems, most notably in the ability to capture the socioeconomic dimensions of food insecurity(25). We have introduced this new information into our composite indexes for food security.

Variables have been subdivided in groups (Table 1): The first group collects indicators that describe determinants of food insecurity, that is, structural conditions likely to worsen food insecurity in the absence of adequate policy interventions, including emergency assistance; the second group includes indicators aimed at capturing outcomes of food insecurity, as can be recorded through inadequate food consumption or anthropometric failures; the third group collects indicators providing information on the vulnerability to food insecurity, as can be gauged

[5] A three-indicators index would be as follows: $[(ax_1)^\rho(bx_2)^\rho(1-a-b)x_3)^\rho]^{-1/\rho}$, where the a and b ranges from 0 to one, and $-1 \leq \rho \leq \infty$.

[6] The database has been released on October 9, 2012, and revised on March 15, 2013. The authors are grateful to the ESS FAO Division for having provided the dataset.

from observing past variability of outcomes and vulnerability to shocks. Within the first two groups, the indicators are further classified based on the dimensions of food insecurity on which they provide information, namely, availability, physical access, economic access (or affordability) and utilization. Our composite indexes reflect the above described theoretical framework.

TABLE 1 ABOUT HERE

As discussed above, constructing a composite index requires several steps that can be listed as follows: defining the phenomenon, selecting the variables, filling missing data, homogenizing the information, weighting information and aggregating information. Nowadays, a vast majority of experts have reached a consensus on the definition of food security, and several authors have provided excellent descriptions(3, 6, 12, 38). We have adopted the FAO guidelines in defining the phenomenon and selecting the variables(16) and have focused our quantitative analysis on comparing different alternatives for the last four steps.

Our first decision concerns how to deal with missing data. Missing data can be random or systematic: The former depends on the variable itself or on other variables of the dataset; the latter depends on the values themselves. Although there are different methods to handle missing data, there is no test to assess the nature of the lack. Common approaches to impute missing data consist of deleting records that contain missing data or imputing missing data by means of ad hoc statistics (e.g., mean, median or regression imputation) or algorithms (e.g., Markov Chain or Monte Carlo algorithm). None of the approaches are exempt by drawbacks; therefore, it is wise to carefully document the selected imputation procedures.

Moving a step forward, we needed to homogenize the information. Due to the heterogeneity of measurements units, each indicator has to be normalized prior to the data aggregation. A wide range of different normalization methods can be applied. The choice should take into account the data properties and the objectives of the index we are constructing(17, 24). Normalization methods include, among others, ranking, standardization, min-max, distance to a reference observation, score function and balance of opinions[34]. All in all, normalization methods allow comparing indicators, bringing different measurement units onto the same dimension. Different methods imply different pros and cons. For instance, the ranking method is extremely simple, robust to outliers and allows comparison among observations, at the cost of losing information on levels. On the contrary, a complex method, such as balance of opinions, may be powerful in order to fill the lack of primary data by mean of experts' opinions, although it would be extremely difficult to replicate the analysis over time and space.

Lastly, the set of selected variables, treated for missing data and normalized, constitutes the ingredients of the composite indexes. The final step consisted of synthesizing the information into a few (or unique) indicators. Different weighting techniques may be chosen, none of which is exempt by a discretionary choice[40]. The most common weighting techniques are derived from statistical models (e.g., unobserved components models) or from participatory methods (e.g., budget allocation, analytic hierarchy processes and conjoint analysis). The choice has to be guided by the theoretical framework underlying the scorecard. For instance, equal weighting implies that indicators (or dimensions) have similar importance, whereas principal components analysis or factor analysis relies on data variability and variables correlation.

Data aggregation follows the weighting. It condenses the information conveyed by indicators into a single index. Two common approaches are the linear aggregation and the geometric aggregation. The former, which is feasible when individual indicators have the same measurement unit, transfers the relative importance of single indicators to the scorecard index. In other terms, it is a conservative measure. On the contrary, geometric aggregations allow taking into account non-compensability between indicators or dimensions.

3.1 Paying attention or not paying attention: How relevant is each decision?

We adopted different methodologies at four "choice nodes":filling missing data, homogenizing the information, weighting information and aggregating information. We tested for two methods to deal with missing data (multiple and simple imputation), two methods to normalize data (z-score and distance from the lowest value[7]), four approaches to weight subindexes (equal weighting, empirical rank correlation, inverse correlation and shrinkage estimation of correlation) and three alternatives to aggregate information (linear aggregation, simple geometric aggregation and CES aggregation[8]).

The experiment lies in comparingchanges in rankings obtained by eight different composite indexes. The baseline scenario consists of the following "choices": multiple imputation, z-score, equal weighting and linear aggregation[9] (Table 2). Each indicator has been normalized to a 0-100 scalefor direct comparison with other indicators.

TABLE 2 ABOUT HERE

We compared the methods in terms of average distance of rankings from the baseline scenario. More precisely, we computed the square root of the difference (in absolute terms) of rankings of country *i* and country *j* under the two methods. The larger the distance induced by selecting an alternative different method, the larger the relevance of the choice and the more accurate the decision-making process should be(Table 3).

TABLE 3 ABOUT HERE

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[7] The latter is adopted to compute theGlobal Food Security Index 2013. The formula is as follows: $z = \frac{x - \min(x)}{\max(x) - \min(x)}$. More information on the GFSI can be found at: http://foodsecurityindex.eiu.com/

[8] Geometric aggregation is intended to capture the hierarchical structure of the phenomenon. As Barrett[(1)] pointed out, "Availability, access, and utilization *[…]* are inherently hierarchical, with availability necessary but not sufficient to ensure access, which is, in turn, necessary but not sufficient for effective utilization." The structure calls for further research on how to aggregate the subindex. An alternative, yet not empirically investigated, is to use a quasi-linear aggregation method or to use a *Stone-Geary-type* function. This is a promising research area.

[9] It is worth noting that most of the proposed indexes (e.g., the Global Food Security Index proposed by the Intelligence Unit and the Global Hunger Index proposed by the IFPRI) are slight variants of our baseline scenario.

Results show that the choice of the methods to compute composite indexes has different relevance. The choice of the normalization and weighting methods are the least relevant; on the contrary, different alternatives for data imputation would lead to different results. Finally, choosing the aggregation formula is the most crucial decision: Diverse formulas provide different composite indexes.

4. Conclusive remarks

The debate on food security is rapidly growing, and it concerns a wide range of disciplines. Its multidisciplinary nature has motivated a tremendous number of researches aimed at measuring the contribution of different aspects of food security. A large variety of indicators have been proposed. However, measuring thephenomenon as a whole is*perse*important. Yet unclear is how analysts should weight the various aspects that contribute to rendering the population of a country *food secure*.

Our analysis aimed at understanding how relevant and discretional may be the analyst's choice of algorithms to compute composite indexes for food security. We have compared different methods to build composite indexes. As seen from Table3, different methods have different impacts on rankings. We show that normalization and weighting are (relatively) less crucial decisions, whereas special attention has to be paid in choosing the data imputation and aggregation methods.

When proposing new composite indexes, the UN, the international agencies or academics and researchers, must pay attention to emphasizing the algorithm implemented to transform raw data into a single index. They need to be aware of the implications that each method conveys. Without transparency on the steps followed to build the index, no judgment or comparison with existing indicators can be made.

Measuring food security through composite indicators is a promising area of research. In particular, our analysis of different methods to build composite indexes may be complemented by experts' evaluations. The synergic responses from quantitative and qualitative analyses would enhance policymakers' awareness in planning target-oriented measures of interventions. This step is left to future researches.

References

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

2. Cafiero, C.,2013. What do we really know about food security? (No. w18861). National Bureau of Economic Research.

3. Caracciolo, F., Santeramo, F. G. (2013). Price Trends and Income Inequalities: Will Sub-Saharan Africa Reduce the Gap?. African Development Review, 25(1), 42-54.

4. Carletto, C., Zezza, A., Banerjee, R., 2012. Towards better measurement of household food security: Harmonizing indicators and the role of household surveys. Global Food Security 2(1), 30–40.

5. CFS, 2009. Reform of the Committee on World of Food Security: Final Version.

6. Chambers, R., 1990. Rapid but Relaxed and Participatory Rural Appraisal: Towards Applications in Health and Nutrition, Paper presented at the International Conference on Rapid Assessment, Pan American Health Organization Headquarters, Washington, D. C.

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

8. De Haen, H., Klasen, S., Qaim, M., 2011. What do we really know? Metrics for food insecurity and undernutrition. Food Policy 36(6), 760-769.

9. De Muro, P., Burchi, F., 2007. Education for Rural People and Food Security. A Cross Country Analysis. Food and Agricultural Organization of the United Nations, Rome.

10. De Muro and Aurino, 2011. Issues in food security measurement. Wye City Group Meeeting, Rio de Janeiro.

11. Dempster, A.P. Rubin D.B., 1983. Introduction, in: Madow, W.G., Olkin, I., Rubin, D.B. (Eds.), Incomplete Data in Sample Surveys. Academic Press, New York, pp. 3-10

12. Economist Intelligence Unit, 2013. The Global Food Security Index 2013: An annual measure of the state of global food security.

13. Food and Agriculture Organization of the United Nations (FAO), 1996. Rome Declaration on World Food Security. World Food Summit, Rome.

14. Food and Agricultural Organization, 2012. New metrics to measure and monitor performance in agriculture and food security. December 2012, Rome.

15. Food and Agricultural Organization, 2013a. The Director-General's Medium Term Plan 2014-17 and Programme of Work and Budget 2014-15. Thirty-eighth Session of the Conference 15 – 22 June 2013.

16. Food and Agricultural Organization, 2013b. New metrics to measure and monitor performance in agriculture and food security", held on 5 December 2012 in Rome.

17. Food and Agricultural Organization, 2013c. The State of Food Insecurity in the World: The multiple dimensions of food security.

18. Freudenberg, M., 2003. Composite indicators of country performance: a critical assessment, OECD, Paris.

19. Gabbert, S., Weikard, H., 2001. How widespread is undernourishment? A critique of measurement methods and new empirical results. Food Policy, 26, 209-228.

20. Gentilini, U., and Webb, P., 2008. How are We Doing on Poverty and Hunger Reduction? Food Policy, 33: 521-532.

21. Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Jules Pretty, Sherman Robinson, Sandy M. Thomas, Toulmin, C., 2010. Food security: the challenge of feeding 9 billion people. Science 327(5967), 812-818.

22. Headey, D., Ecker, O., 2013. Rethinking the measurement of food security: from first principles to best practice. Food security 5(3), 327-343.

23. Hoddinott, J., and Yohannes, Y., 2002. Dietary Diversity as a Food Security Indicator, FCND Discussion Paper No. 136, IFPRI. International Food Policy Research Institute, Washington, D. C.

24. IFPRI/ Concern/ Welthungerhilfe, October 2011. Global hunger index – the challenge of hunger: taming price spikes and excessive food price volatility. Bonn, Washington, DC, Dublin.

25. Jacobs, R., Smith, P., Goddard M., 2004. Measuring performance: an examination of composite performance indicators, Centre for Health Economics. Technical Paper Series 29.

26. Jones A. D., Ngure F. M., Pelto G., Young S. L., 2013. What Are We Assessing When We Measure Food Security? A Compendium and Review of Current Metrics. Advances in Nutrition 4, 481-505.

27. Lintelo, D. J. H., 2012. Measuring Political Commitment to Reducing Hunger and Under-nutrition: can it be done and will it help? IDS Bulletin, 43(S1): 65-73.

28. Little, R.J.A., Rubin D.B., 2002. Statistical Analysis with Missing Data, Wiley Interscience, J. Wiley &Sons, Hoboken, New Jersey.

29. Manski, C. F., 2003. Partial identification of probability distributions. Springer.

30. Mas-Colell, A., Whinston, M. D., Green, J. R., 1995. Microeconomic theory. Oxford university press, New York.

31. Masset, E., 2011. A Review of Hunger Indices and Methods to Monitor Country Commitment to Fighting Hunger. Food Policy 36, S102-S108.

32. Mock, N., Morrow, N., Papendieck, A., 2013. From complexity to food security decision-support: Novel methods of assessment and their role in enhancing the timeliness and relevance of food and nutrition security information. Global Food Security 2(1), 41-49.

33. Moron, C., and Viteri, F. E., 2009. Update on Common Indicators of Nutritional Status: food access, food consumption, and biochemical measures of iron and anemia, Nutrition Reviews*,* 67(S1): 531-535.

34. Munda G., 2012. Choosing aggregation rules for composite indicators. Social Indicator Research 109(3), 337-354.

35. Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., Giovannini, E., 2005a. Handbook on constructing composite indicators: methodology and user guide (No. 2005/3). OECD publishing.

36. Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., 2005b. Tools for composite indicators building. European Comission, Ispra.

37. Pangaribowo E. H., Gerber N., Torero M., 2013. Food and Nutrition Security Indicators: A Review. FOODSECURE working paper 04.

38. Pérez-Escamilla, R., 2013. Can experience-based household food security scales help improve food security governance? Global Food Security 1, 120-125.

39. Pinstrup-Andersen P., 2009. Food security: definition and measurement. Food Security 1, 5–7.

40. Quisumbing, A. R., 2013. Generating evidence on individuals' experience of food insecurity and vulnerability. Global Food Security 2,50-55.

41. Saaty, T. L., 2001. Decision Making for Leaders: The Analytic Hierarchy Process for Decisions in a Complex World: 1999/2000 Edition (Vol. 2). RWS publications.

42. Schafer, J., 2002. Dealing with missing data.

43. Svedberg, P., 2011. How Many People are Malnourished? Annual Review of Nutrition, 31: 263-283.

44. Wheeler, T., von Braun, J., 2013. Climate change impacts on global food security. Science 341(6145), 508-513.

Table 1 - List of variables for Food Security Composite Indexes

DETERMINANTS (INPUTS)	
Availability	
	Average Dietary Energy Supply Adequacy
	Average Value of Food Production
	Share of dietary energy supply derived from cereals, roots and tubers
	Average protein supply
	Average supply of protein of animal origin
Physical access	
	Percent of paved roads over total roads
	Rail-lines density
	Road density
Economic access	
	Domestic Food Price Level Index
Utilization	
	Access to improved water sources
	Access to improved sanitation facilities
OUTCOMES	
Inadaquate access to food	
	Prevalence of undernourishment
	Share of food expenditure of the poor
	Depth of the food deficit
	Prevalence of food inadequacy
Utilization	
	Percentage of children under 5 years of age who are stunted
	Percentage of children under 5 years of age affected by wasting
	Percentage of children under 5 years of age who are underweight
	Percent of adults who are underweight
VULNERABILITY/STABILITY	
	Domestic food price level index volatility
	Per Capita food production variability
	Per Capita food supply variability
	Political stability and absence of violence/terrorism
	Value of food imports over total merchandise exports
	Percent of arable land equipped for irrigation
	Cereal import dependency ratio

Table 2- A roadmap to build FS composite indexes

	Steps	Baseline methods	Alternative methods
1	Defining the phenomenon	*FAO definition*	
2	Selecting the variables	*FAO guidelines*	
3	Filling missing data	*Multiple imputation*	*Single imputation*
4	Homogenizing the information	*Z-score normalization*	*Normalization*
5	Weighting information	*Equal weighting*	*Rank correlation / shrinkage*
6	Aggregating information	*Linear aggregation*	

Table 3 – Relevance of the choice

			Relevance*
Filling missing data			
Multiple imputation	vs	Simple Imputation	**4**
Homogenizing the information			
Z-score	vs	Normalization	**2**
Weighting information			
Equal weighting	vs	Rank correlation	**3**
Equal weighting	vs	Inverse correlation	**1**
Equal weighting	vs	Shrinkage correlation	**3**
Aggregating information			
Linear aggregation	vs	Geometric aggregation	**5**
Linear aggregation	vs	CES aggregation	**5**

* The larger the value, the larger the relevance of the choice (i.e. large change in rankings with respect to the baseline composite index).