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The measurement of household food security: Correlation and latent variable analysis of alternative indicators in a large multi-country dataset

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1. Introduction

Food security is again at the center of the international development discourse, both as a means to facilitate achievement of health goals and as an end in itself (Hall et al., 2011; United Nations, 2015). This renewed focus has revived longstanding debates about how to best measure food security (Barrett, 2010; Cafiero, 2012; Coates, 2013; Carletto et al., 2013; Headey and Ecker, 2013; Maxwell et al., 2014; Vaitla et al., 2015.[1])

Food security is a theoretical construct—a "latent variable"—that can only be measured indirectly. The most frequently cited definition of the concept comes from the 1996 World Food Summit: "food security exists when all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO Statistics Division, 1996). This definition includes a variety of dimensions, including universality, persistence through time, physical access, economic access, sufficiency, safety, and preferences, all of which could be considered "dimensions" of food security. These dimensions are distinct but not necessarily independent; for example, people may consume sufficient amounts of food only if they have economic access. While the definition quoted above is commonly accepted by the international humanitarian and development community, no similar consensus exists on how to identify and categorize the dimensions of food security.

The multidimensionality of food security complicates its measurement. The choice of which indicator(s) of food security to use in a given situation is typically informed by factors including specific measurement objectives (e.g., early warning, assessing the impact of assistance), level of food insecurity, measurement ease, budgetary considerations, and security and political constraints, though not necessarily by a complementary, clear understanding of which dimension(s) of food security the selected measures capture. This can lead to serious problems, especially in the measurement of acute food insecurity, for which the consequences of misclassification can be particularly serious.

The Integrated Food Security Phase Classification's (IPC's) Acute Food Insecurity Reference Table for Household Group Classification uses the Coping Strategies Index (CSI), Food Consumption Score (FCS), Household Dietary Diversity Score (HDDS), and Household Hunger Scale (HHS) as proxy measures of household food consumption (IPC Global Partners, 2012). The World Food Programme relies heavily on FCS, although it sometimes also uses CSI (WFP, 2009), or, in more recent years, the reduced CSI (rCSI). USAID's Office of Food for Peace development projects typically apply HDDS and/or HHS (Swindale and Bilinsky, 2006; Coates et al., 2007; Ballard et al., 2011).

The objective of the present paper is to identify improved ways of measuring food insecurity through an investigation of the extent to which four commonly used food security indicators gather distinct information. The indicators we focus on are: (1) FCS, (2) HDDS, (3) rCSI, and (4) HHS, all of which are often used both in humanitarian emergencies and development contexts. Logical arguments for the distinct nature of food security indicators have been made in the literature (see, for example, Coates, 2013), but empirical tests are rare, and to our knowledge none exist using datasets of this size and geographical breadth. We analyze the relationships among the four indicators using a large pooled dataset that integrates information from 21 household surveys conducted

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[1] The analysis presented here builds from the study, "Comparing Household Food Consumption Indicators to Inform Acute Food Insecurity Phase Classification." That study was made possible by the generous support of the American people through the support of the Office of Health, Infectious Diseases, and Nutrition, Bureau for Global Health, U.S. Agency for International Development (USAID) and the Bureau for Africa, under terms of Cooperative Agreement No. AID-OAA-A-12-00005, through the Food and Nutrition Technical Assistance III Project (FANTA), managed by FHI 360. Additional support was provided by the USAID-funded Famine Early Warning Systems Network (FEWS NET) activity, managed by Chemonics International, Inc. under Contract No. AID-OAA-I-12-00006. The authors thank the many organizations that provided their datasets for use in that study, as well as the present analysis.

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between 2008 and 2013 in ten countries: Ethiopia, Haiti, Kenya, Mongolia, Pakistan, Somalia, South Sudan, Sudan, Uganda, and Zimbabwe. Specifically, we first look at bivariate correlations among the typically used forms of these indicators, and then concordance among their categorical versions. We then utilize exploratory factor analysis (EFA) to assess the dimensionality of these indicators. Specifically, EFA hypothesizes that the observed correlations between indicators are due in part to their common associations with unobserved latent variables, which can be interpreted as underlying dimensions of food security. This approach thus extracts more information about relationships between measurement indicators than correlation analysis does alone.

Section 2 reviews previous literature on the association of FCS, HDDS, rCSI, and HHS with each other and with other measures of food access—a key aspect of food security—and briefly reviews the limited body of past work using factor analysis (FA) or related techniques to extract food security dimensionality. Section 3 describes the data used in this study. Section 4 outlines the EFA approach we utilize. Section 5 presents bivariate correlations, categorical concordance, and the results of the EFA. Section 5 interprets these results in light of the ongoing debates about food security measurement, and discusses implications for policy and further research. Section 6 presents conclusions.

2. Previous work

Numerous studies have addressed the question of the comparability of different measures of food security. Several different categories of food security measures have been developed, e.g., measures of nutritional status, caloric intake, dietary diversity, behaviors or experience, expenditure, and self-assessment measures (Cafiero et al., 2014; Barrett, 2010; Cafiero, 2012; Coates, 2013; Carletto et al., 2013; Headey and Ecker, 2013; Maxwell et al., 2014; Vaitla et al., 2015; Upton et al., 2016). Unfortunately, there is currently no "gold standard," clinical or otherwise, by which to judge the validity and reliability of these indicators (Coates, 2013). Despite its importance as an outcome, nutritional status is generally not used as a measure of food security because of issues of complex causality—care practices and the health environment, not food security alone, are important determinants of nutritional status. Individual dietary energy intake measures are usually too costly, both in terms of time and money, to be used for most applications beyond basic research; even when carried out, evidence suggests that these measurements often underestimate energy intake (Arsenault, 2015). Indicators based on the frequency of food groups consumed and behavioral/experiential measures have emerged as the two most common classes of food security measurement—largely because they are feasible in practice—but they can produce very different estimates of the prevalence of food insecurity (Maxwell et al., 2014; Headey and Ecker, 2013).

A variety of one-to-one comparisons have been made among these indicators, and several attempts have been undertaken to relate dietary diversity and behavioral measures to caloric intake, on the assumption that even if the latter measure is not a "gold standard," it is at least objectively measurable. These studies have produced differing results (Maxwell et al., 1999; Christiaensen and Boisvert, 2000; Coates et al., 2007; Wiesmann et al., 2009; Becquey et al., 2010; Lovon and Mathiassen, 2014), which are reviewed in detail elsewhere (Coates, 2013; Headey and Ecker, 2013; Vaitla et al., 2015). Although some of these works have argued that one of these indicators—or classes of indicators—perform(s) better than others in proxying for caloric intake, none has squarely addressed the practical problem of how consistently different indicators provide similar estimates of food insecurity and what should be done if they do provide contradictory results, especially under time-constrained programmatic circumstances. Jones et al. (2013) made suggestions as to the most appropriate food security measures for some applications, but they did not suggest means of synthesizing different indicators. Carletto et al. (2013) suggested a harmonized "dashboard" of indicators.

A small set of past studies have used FA or a related technique, principal components analysis (PCA), to analyze food security dimensionality (see Section 4.1 for a discussion of the key differences between FA and PCA). A study by Coates et al. (2003) used PCA to assess the dimensionality of the "Food Access Survey Tool" (FAST) scale, an instrument originally developed for Bangladesh that later led to the development of the now widely used Household Food Insecurity Access Scale (HFIAS) (itself the parent tool of the HHS, which contains a subset of three HFIAS questions). They extract two factors, the first of which pertain to the quantity, quality, acceptability, and stability of households' food access, and a second factor that contains three items reflecting aspects of diet quality. Knueppel et al. (2009) examine data collected in rural Tanzania using the HFIAS. They use PCA to extract two components, which the authors theorize to represent insufficient food intake and insufficient food quality. The analysis also found that the HHS subset of questions—which ask about the most severe manifestations of food insecurity—associate strongly with the food intake factor and weakly with the quality factor.

Lorenzana and Sanjur (1999) develop a household food insecurity scale based on responses of peri-urban residents of Caracas, Venezuela to 12 questions about reduction in the number and size of meals, eating less preferred food, and complaints of hunger. The authors report the retention of two factors in their analysis, the first of which is interpreted as "altered food intake" and the second as "hunger experiences of adults and children." The first factor is associated most strongly with fewer meals, smaller meal sizes, and lack of money to buy food. The second factor is associated with complaints of hunger and going to bed hungry. The authors find that the two factors are also well correlated with income, energy availability, and social class. Banna and Townsend (2011) perform PCA on a 23-question "food behavior" checklist administered to 154 low-income Spanish-speaking women in California. The questions cover the quantity and frequency of fruit, vegetable, dairy, meat, fast food, and beverage consumption, as well as several additional questions about food stocks, usage of food labels, and eating habits. They extract four components corresponding to fruit/vegetable consumption, diet quality), fast food consumption, and sweetened beverage consumption.

Several key themes emerge from this review of the food security measurement literature. First, the correlation coefficients among different food security indicators vary from relatively weak to relatively strong, suggesting that they may be capturing different dimensions of the complex construct of food security, may be sensitive to food insecurity only in particular ranges of severity, or may be subject to other inconsistencies in measurement and statistical assumptions. Second, although the continuous versions of these indicators are relatively well correlated in some contexts, the variables are frequently used in categorical form, and the categorical measures of these indicators provide widely varying estimates of the prevalence of food insecurity (Maxwell et al., 2014; Vaitla et al., 2015).

Third, to date few efforts exist to extract latent dimensions from collections of food security items, and none utilize large multi-country datasets. All of these issues can have serious consequences for assessment, resource allocation, and impact evaluation. Thus far, despite the validation studies just cited, practical advice has been limited with regard to the selection of indicators for food security measurement, and, particularly in the context of acute food insecurity, actual practice remains variable. In the absence of a "gold standard" or a single, clearly preferred indicator, further investigation of the practical means of improving food security measurement is needed.

3. Data

3.1. Measurement variables

We explore four food security measurement variables in this study: FCS, HDDS, rCSI, and HHS.[2] Two other commonly collected food security indicators, the CSI and HFIAS, are not considered because of lack of available data within the study datasets—that is, datasets in which they appear with at least one other food security indicator. However, the rCSI is comprised of five coping strategies questions (those considered most universally applicable) commonly included in the CSI (Maxwell and Caldwell, 2008). In addition, as noted above, the HHS is a subset of HFIAS; the three HFIAS questions included in HHS ask about very severe manifestations of food insecurity. As described in the paragraphs below, each of the four indicators is actually a composite, comprised of multiple constituent "items" (see Appendix A for the list of items within each indicator) (see Table A1).

FCS. The FCS asks about the number of food groups (of 8 total groups) consumed by anyone in the household over the past week (ODAV-WFP, 2008). The food groups are weighted to produce a composite score that reflects WFP's perception of nutrient density. The group (with weights in parentheses) are: staples (2), pulses (3), vegetables (1), fruit (1), meats, eggs, and fish (4), dairy products (4), sugars (0.5), and oils/fats (0.5). Each group is multiplied by its weight and the number of days consumed by any household member over the past week. The weighting and frequency steps allow FCS to be potentially used as a measure of the frequency of food group consumption at the household level, not only as a measure of household dietary diversity. The possible range for the composite indicator is 0–112. Where sugars and oils/fats *are not* consumed daily, scores > 35 are considered acceptable, 21–35 borderline, and < 21 poor.[3] These cut-offs are based on WFP internal decision-making; little empirical work has tested the appropriateness of these cutoffs with respect to a detailed nutrient intake over time.

HDDS. The HDDS focuses on household dietary diversity (Swindale and Bilinsky, 2013), with a design that presumes that as households afford a more diverse diet, they are able to access a greater quantity of food. Three key factors that differentiate HDDS and FCS are: (1) the HDDS considers only the last 24 h instead of the past week; (2) the HDDS considers 12 food groups—cereals, root and tubers, vegetables, fruits, meat and poultry, eggs, fish and seafood, pulses and legumes, milk/dairy products, fat and oil, sugar, and other miscellaneous foods; and (3) the HDDS food groups are unweighted. The composite HDDS thus ranges from 0 to 12. No guidelines currently exist on interpreting the score in terms of food security status. Vaitla et al. (2015) broadly follow the HDDS cut-offs used in the acute IPC and suggest 0–3 (severely food insecure), 4–5 (moderately food insecure), and 6–12 (food secure/mildly food insecure) as possible categories, and we employ these in the analysis that follows in Section 5. These cut-offs, however, require theoretical and empirical validation, especially evaluation of whether the proposed thresholds can be applied universally.

rCSI. As previously noted, the rCSI comprises a small set of coping behaviors, and associated severity levels that are believed to be applicable more universally (Maxwell and Caldwell, 2008). The rCSI items capture information about eating less preferred but cheaper foods (with a relative weight of 1), reducing the number of meals per day (1), limiting portion size at mealtime (1), prioritizing consumption for certain household members (e.g., limiting adult intake) (3), and borrowing food/money from friends and relatives (2). Each item asks about frequency, measured in days, over the past week. The weighted frequencies are then summed for a possible range of 0–56. No universal guidelines for categorical interpretation of rCSI scores currently exist, although Maxwell et al. (2014) have suggested 0–4 (food secure/mildly food insecure), 5–10 (moderately food insecure), and $\geq$11 (severely food insecure) as provisional categorical bounds, subject to further validation. We use these in the categorical analysis of Section 5.

HHS. The HHS focuses on the subset of HFIAS questions that are considered the most universally interpretable and most severe (Ballard et al., 2011). The three questions ask the frequency of the following experiences over the past month: having no food of any kind in the household; going to sleep hungry because there was not enough food; and going a whole day and night without eating. The possible responses are "never", "rarely" (1–2 times), "sometimes" (3–10 times), and "often" (>10 times), and the respective weights for the responses are 0 (never), 1 (rarely and sometimes), and 2 (often). The composite range is thus 0–6, with 0–1 signifying "little to no hunger," 2–3 "moderate hunger," and 4–6 "severe hunger." Note that this is the language used by the methods manual for the HHS (Ballard et al., 2011); for the purposes of this analysis, "hunger" equates with "food insecurity."

Note a few important differences in the design of the variables. The FCS and HDDS capture household dietary diversity, and some studies argue that FCS effectively proxies quantity of food consumption at the household level (Wiesmann et al., 2009; Headey and Ecker, 2013), though some of the validation studies for FCS note a high degree of contextual variation in the correlation between FCS and household caloric intake (Lovon and Mathiassen, 2014). The rCSI focuses on behavioral responses to scarcity, and HHS asks about extremely severe experiences. The time scales vary as well: HDDS asks about the last 24 h, FCS and rCSI ask about the past week, and HHS asks about the past month.

3.2. Data sources

The data for this analysis was originally compiled for the Household Food Consumption Indicators Study (HFCIS), initiated and overseen by USAID's Food and Nutrition Technical Assistance III Project (FANTA) and the Famine Early Warning Systems Network (FEWS NET) (Vaitla et al., 2015). Inclusion criteria for candidate datasets were: (1) datasets contained sufficiently high-quality, clean data on at least two food security indicators among the set of FCS, HDDS, rCSI, and HHS; (2) samples were statistically representative of a given population group, varying in administrative unit size from country-level to district-level samples, with a focus on rural and food insecure populations; (3) the metadata included clearly articulated information on data collection methods, protocols, and instruments; and (4) sample size was at least 200 for any single indicator. In all, we obtained 65,089 observations from 21 survey datasets and 10 countries (see Fig. B1 in Appendix B) and integrated them into a single pooled dataset. The number of pairwise observations within the set of four indicators varies between a low of 7550 for FCS-HDDS and a high of 32,649 for

[2] We focus in much of this paper on food security indicators expressed in their original (quantitative) form, and examine in particular the possibility that these indicators are measuring different latent dimensions of food security. With respect to the categorical forms of these indicators, two other important reasons for the lack of association may be: (1) strong sensitivity to the choice of categorical threshold values (i.e., categories are poorly aligned across indicators) and (2) the inability of some indicators to pick up variation at relatively mild or relatively severe levels of food insecurity. These issues are explored in other work using the same dataset (Vaitla et al., 2015).

[3] Where sugars and oils/fats *are* consumed daily, scores >42 are considered acceptable, 28–42 borderline, and <28 poor.

rCSI-FCS. Note that the analyses below rely largely on pairwise comparisons; only three of the 21 datasets contain all four indicators. Appendix B provides more details on the data sources. While we do not claim that the results of this analysis are globally generalizable—a limitation discussed in the conclusion—the size and scope of this dataset are much larger than in any previous work on this topic.

4. Methodology

4.1. Exploratory factor analysis

If the various indicators are measuring the same phenomenon—i.e., the same underlying dimension of food security—or measuring closely related phenomena, they are likely to be strongly correlated. Reflective latent variable models, the type we employ in this study, make the interpretation of correlation explicit: "latent variables"—the underlying dimensions—are assumed to generate the observed correlation structure of the measurement indicators. We perform EFA to model the relative association of each unobservable dimension on each food security indicator. Note, however, that while factor analysis can help reconstruct the latent structure of dimensionality, it cannot identify exactly what the dimensions *are*; the labeling of dimensions depends on conceptual judgment. We reserve our discussion of what these latent dimensions may represent for Section 6.

FA enables broader inferences than can be made from looking at the correlation structure of the measurement variables alone. As noted above, strong correlation between indicators can be a result of different variables providing information about the *same* underlying dimension of food security, or it can reflect the capture of *unique but correlated* information. FA extracts more information from the correlation structure by hypothesizing underlying distinct dimensions, and quantifies the strength of relationships between each measurement variable and each of these underlying "dimensions," as well as the association between dimensions. Partitioning variance in this way thus allows an understanding of whether the observed correlation between food security variables is due to the relationship between latent dimensions.

Given the use of PCA in similar analyses, a brief justification for the use of FA is warranted, as the two approaches differ in important ways. FA presumes that the measurement indicators themselves co-vary for reasons independent of the underlying latent dimensions; that is, part of the total variance of each measurement indicator is accounted for through covariance with other measurement indicators, not only covariance with the underlying dimensions and the specific and error (i.e., unexplained) variance of the indicators themselves. PCA, on the other hand, is primarily a data reduction method, and as such forces the extracted components to orthogonally explain all variance in the indicators. Outside of these extracted components, covariance between measurement variables is not preserved in PCA.

There are also important distinctions to be made within the family of FA approaches. We concentrate here on two analytical choices: EFA versus confirmatory factor analysis (CFA), and oblique versus orthogonal rotation. EFA does not hypothesize the underlying latent variable structure; neither the number of factors (underlying dimensions) nor the relationships between factors and indicators is constrained. CFA does hypothesize such a structure, and thus constrains each indicator to be associated with only one factor. With respect to rotation, FA does not produce unique solutions; results can be "rotated" to yield solutions that are more easily interpretable or have other desirable properties. Oblique rotation methods allow the underlying factors to be correlated, while orthogonal rotation forces the underlying factors to be as weakly correlated as possible. In this study, we perform EFA with oblique rotation; as noted earlier, insofar as the underlying factors represent food security dimensions of the type found in the World Food Summit definition, we expect factors to be partially overlapping in their informational content.

4.2. The model

In this study, we use EFA to extract associations between latent underlying dimensions of food security and the four composite indicators studied: FCS, HDDS, rCSI, and HHS. The goal of the analysis is to quantify the extent to which these indicators provide unique information about food security. Fig. 1 illustrates the EFA indicator model graphically. The squares represent measurement variables (Y_i; the food security indicators), and the circles represent latent variables (η_i; the underlying dimensions). (Two latent variables are shown here for illustration, but we test EFA models

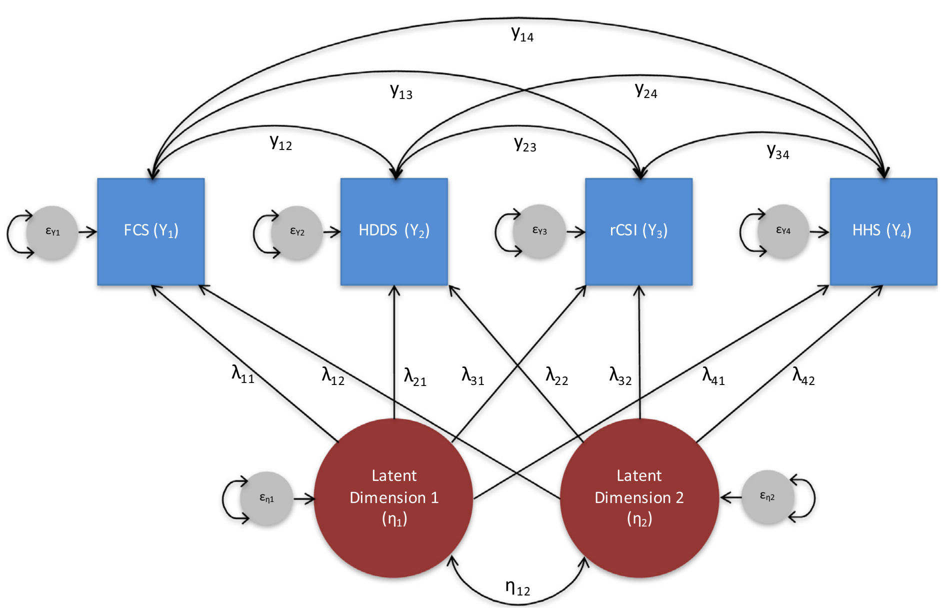

Fig. 1. Path diagram of indicator model.

with varying numbers of theorized factors). The parameters defining the links between the measurement variables at the top of the diagram (denoted by y_{12}, y_{13}, ... , y_{34}) are correlation coefficients, built from a covariance matrix of the four food security variables in question. The parameters linking measurement and latent variables, extracted by the EFA and denoted by λ, represent the structure coefficients (or "loadings") of the model. The total variance of a measurement variable explained by all the latent factors in the model is referred to as the "communality" of that variable, and is similar to an R-squared value in other linear regression models. Error terms (ε) for each measurement variable are also shown; this is the portion of each measurement variable's variance that is not explained by covariance either with other measurement variables or the latent variables (termed "uniqueness"). The loops shown on the latent variables represent variance. The correlation coefficient η_{12} between the two dimensions is also shown.

FA thus estimates the following model from the data:

$$\boldsymbol{y} = \boldsymbol{\Lambda}\mathbf{H} + \mathbf{E} \tag{1}$$

The matrix of measurement indicator values $\mathbf{y}$ is a function of the latent variable matrix $\mathbf{H}$, weighted by the structure coefficient matrix $\boldsymbol{\Lambda}$, added to the residual matrix $\mathbf{E}$. Although $\mathbf{H}$ is unobserved, Eq. (1) implies that the correlation matrix $\mathbf{R}$ of the measurement variables will take the form

$$\mathbf{R} = \boldsymbol{\Lambda}\boldsymbol{\Phi}\boldsymbol{\Lambda} + \boldsymbol{\Psi} \tag{2}$$

where $\boldsymbol{\Phi}$ is the factor correlation matrix and $\boldsymbol{\Psi}$ is the measurement variable residual variance matrix. Measurement variable residual variances must be uncorrelated with each other and with latent variables, and distributed with mean zero. Estimation of $\boldsymbol{\Lambda}$ (pattern loadings) and $\boldsymbol{\Gamma} = \boldsymbol{\Lambda}\boldsymbol{\Phi}$ (structure loadings) proceeds iteratively, with an initial estimate of $\widehat{\boldsymbol{\Psi}}$, subsequent estimates of $\hat{\boldsymbol{\Lambda}}$ and $\widehat{\boldsymbol{\Phi}}$ based on the eigenvectors and eigenvalues from $\mathbf{R} - \widehat{\boldsymbol{\Psi}}$, and updated estimation of $\widehat{\boldsymbol{\Psi}}$ until the difference between present and previous $\widehat{\boldsymbol{\Psi}}$ is less than the associated residual of Eq. (1). Note that we assume in Eqs. (1) and (2) that the indicators can be interpreted as continuous variables, a limitation of the study discussed at greater length in the final section. The supporting information shows outputs from an FA conducted on a matrix of polychoric correlations of the four indicators (Table C1 in Appendix C), which suggests that the results reported below are robust. We utilize the *psych* package in R to implement a minimum residuals (minres) solution, an unweighted least squares approach (R Core Team, 2013; Revelle, 2016).

5. Results

5.1. Description of individual datasets

We first take a closer look at differences across the household survey datasets that comprise the pooled dataset. Fig. 2 shows boxplots for each food security indicator, disaggregated by source dataset. The red line indicates the cutoff for severe food insecurity, the orange line for moderate food insecurity. Only one dataset (Sudan BNSK 2013) has a median FCS value that indicates poor food consumption, and only Zimbabwe 2012 and Uganda Otuke

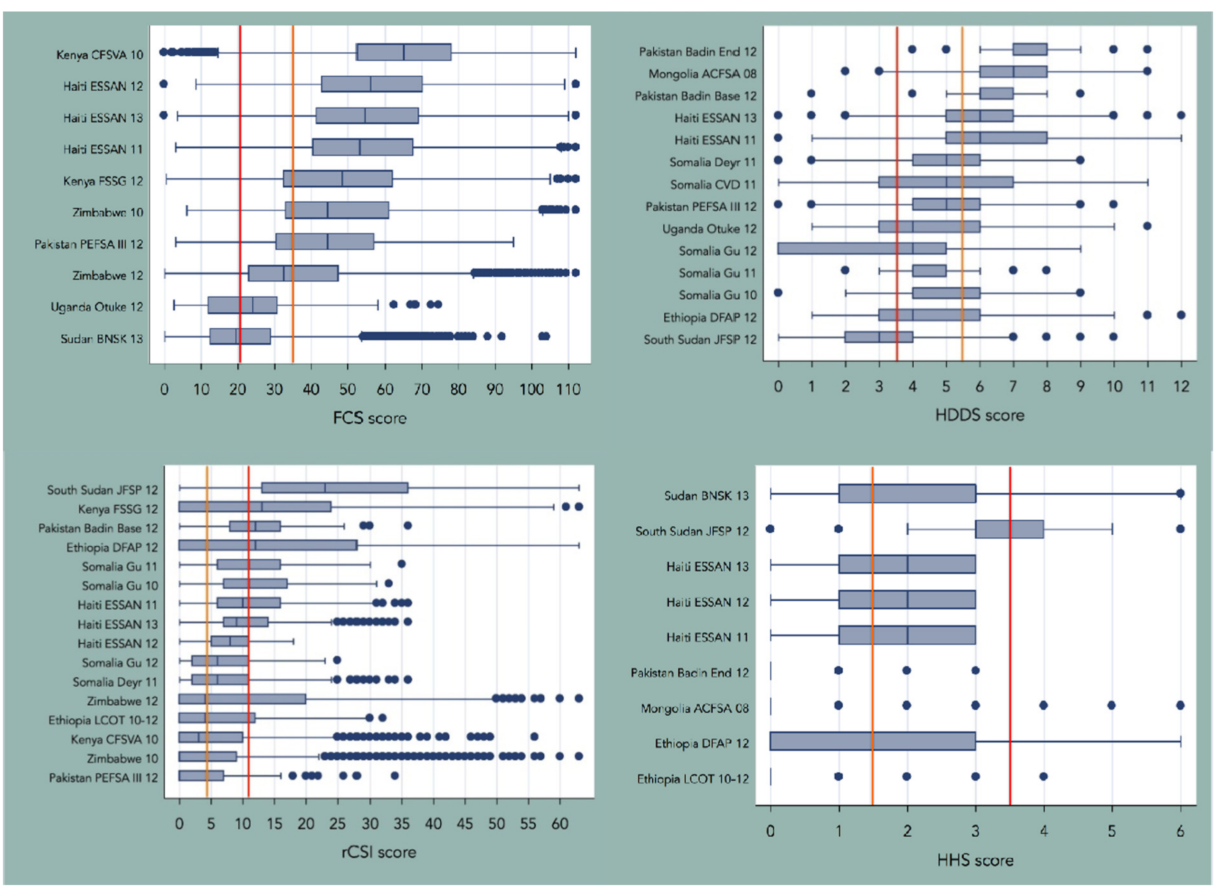

Fig. 2. Boxplots of food security indicators, disaggregated by survey dataset. The box indicates the interquartile range; the median appears as black line inside the box. Outliers (points with values >1.5 times the interquartile range below the first quartile and above the third quartile) are shown as solid dots. Red and orange lines indicate categorical thresholds for severe and moderate food insecurity, respectively. Note that for FCS and HDDS a higher score implies improved food security, whereas for the rCSI and HHS a higher score implies deteriorated food security. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2012 fall in the borderline food consumption category. The HDDS boxplots show that the median household in the South Sudan JFSP 2012 survey is severely food insecure, and median households in nine other countries are moderately food insecure (according to the categorization noted above). In contrast, the median household in 6 of the 16 datasets in which rCSI observations are available is severely food insecure. Only South Sudan JFSP 2012 has a median HHS value at the moderate/severe hunger threshold. Some similarities emerge across all the food security measurement variables; for example, all indicators show that food insecurity is most severe in Sudan and South Sudan. The differences across variables, however, are striking.

5.2. Bivariate correlations

Fig. 3 summarizes bivariate associations between the four food security indicators under study. The upper diagonal shows non-parametric (Spearman's ρ) correlation coefficients across indicator pairs in the pooled dataset; the lower diagonal shows scatterplots with a Lowess smoother (with smoothing parameter $f = 2/3$). The diagonal provides histograms of indicator values.

FCS and HDDS are strongly correlated ($\rho = 0.59$), as might be expected given the similarity of their constituent questions. The relationship maintains a constant slope throughout the range of the indicators. rCSI and HHS are also well-correlated ($\rho = 0.49$), a perhaps unexpected finding given that rCSI is thought to capture relatively less severe coping behaviors and HHS relatively more severe experiential states; a positive correlation mainly holds at lower levels of both indicators, and flattens as HHS values exceed 2 and rCSI values exceed 15. FCS shows moderate association with rCSI and HHS ($\rho = -0.23$ and -0.28, respectively), and this relationship holds throughout the range of the indicators. HDDS is weakly associated with both rCSI ($\rho = -0.14$) and HHS ($\rho = -0.07$). Note that the negative correlation between the dietary diversity indicators (FCS and HDDS) and the behavioral/experiential indicators (rCSI and HHS) is expected, because in one case (dietary diversity) a higher score implies improved food security, whereas for the other (behavioral/experiential) a higher score implies deteriorated food security.

5.3. Categorical concordance

We now turn to the categorical versions of the indicators and examine "concordance," the extent to which different variables place households in the same food security category. Fig. 4 shows concordance across all pairs of indicators. Two patterns are evident. First, pairwise concordance, even within the same pair of indicators, is extremely variable across datasets. For example, HDDS-HHS concordance is high in the Pakistan Badin Endline 2012 and the Mongolia ACFSA 2008 surveys, but low in the South Sudan JFSP 2012 and Ethiopia DFAP 2012 datasets. Second, discordance by two categories—when one measurement variable

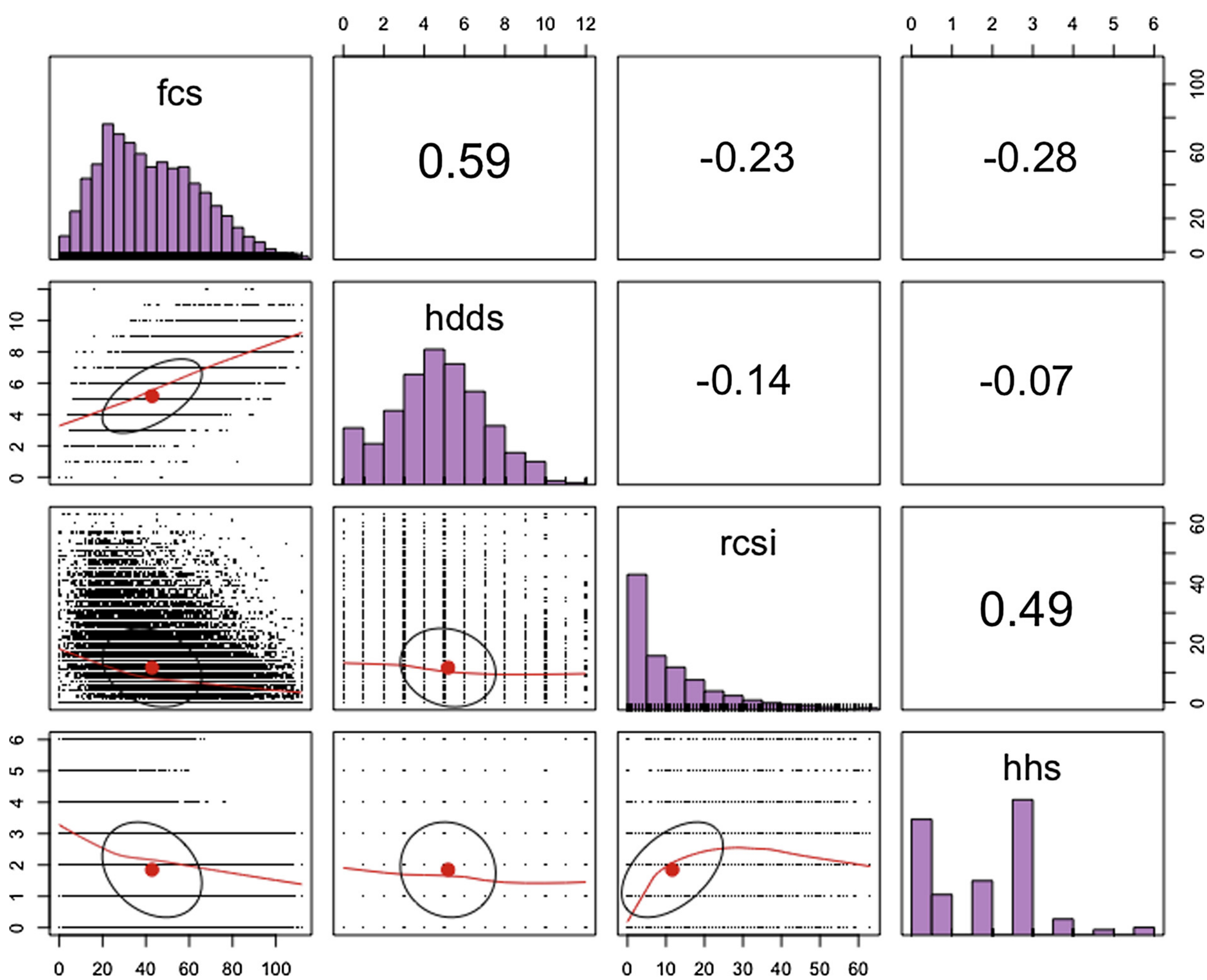

Fig. 3. Spearman's ρ correlation matrix for food security indicators. All correlations are significant at $p < 0.001$. Points in the scatterplots show variable means; ellipses show one standard deviation around the variable means. The font size of the correlation coefficient represents the strength of the absolute value of the correlation.

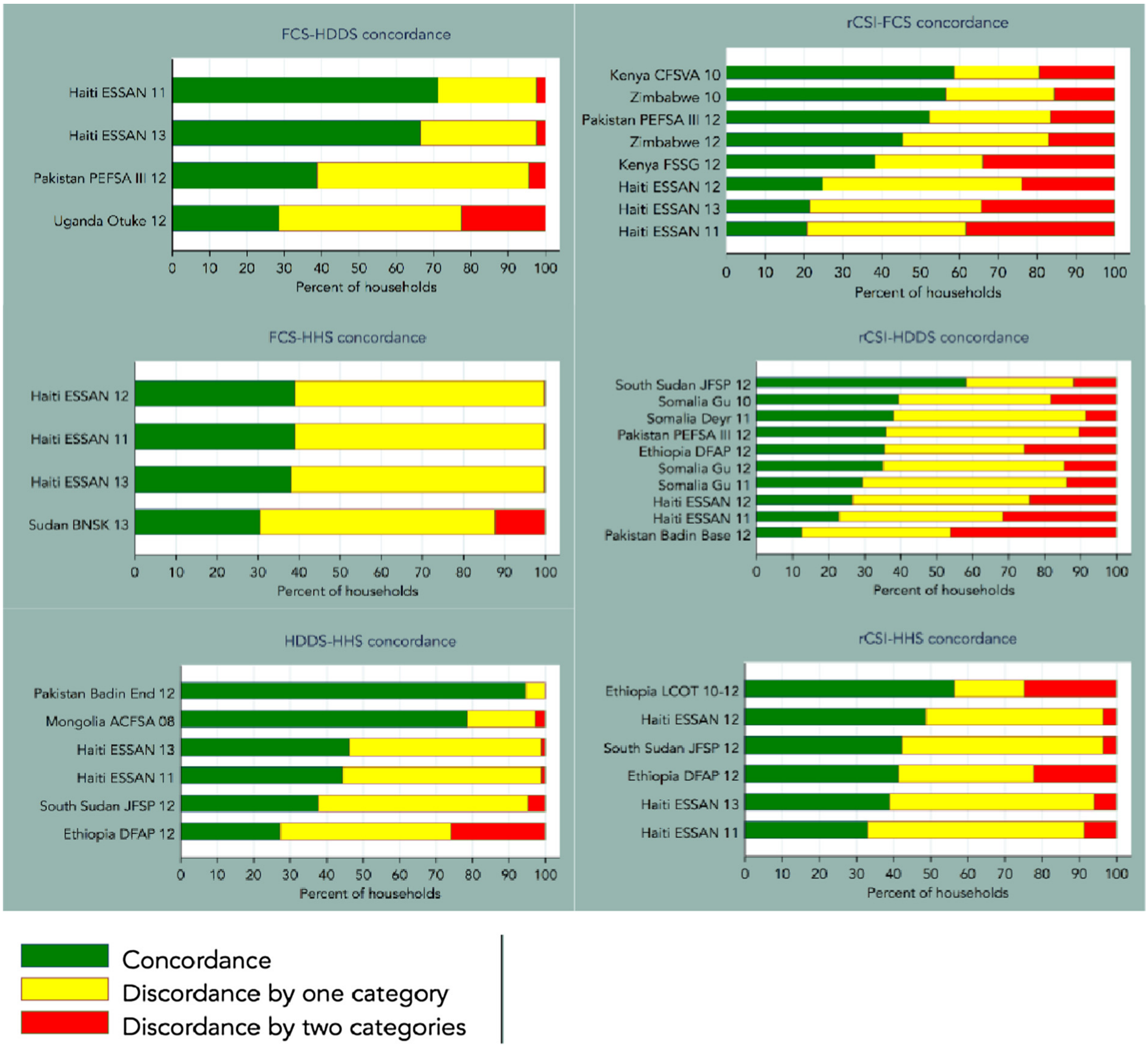

Fig. 4. Categorical concordance.

indicates food security and another indicates severe food insecurity—is surprisingly high, particularly in the rCSI-FCS and rCSI-HDDS pairings.

5.4. Factor analysis results

The strength of correlations shown in Fig. 3 suggest reasonable factorability of the indicator variables. Bartlett's test of sphericity is significant at $p < 0.01$, though the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy yields a fairly low overall value of 0.54. Examination of parallel analysis and Very Simple Structure (VSS) plots suggests a two-factor model. We tested models with fewer and greater numbers of factors, but report only the two-factor results here.

Fig. 5 graphically displays the structure coefficients (standardized loadings) of each variable onto the two hypothesized latent dimensions (MR1 and MR2). FCS and HDDS load strongly onto one dimension and rCSI and HHS onto a second dimension. Table 1 provides more detailed results. Appendix C shows the results of a similar FA conducted on a matrix of polychoric correlations between the indicators.

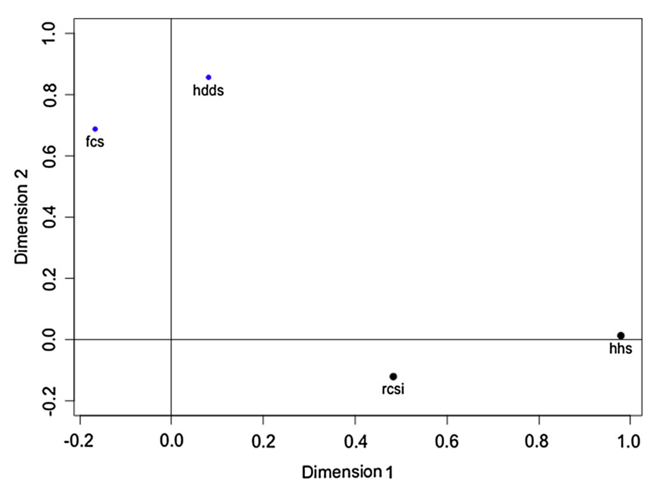

Fig. 5. Standardized loadings of each food security variable onto latent factors MR1 and MR2. The axes show the strength of correlation coefficients (loadings) between indicators and latent dimensions.

We see that HDDS and FCS are essentially uncorrelated with Dimension 1, and rCSI and HHS uncorrelated with Dimension 2.

Table 1
Summary of indicator model results.

Standardized loadings	Dimension 1	Dimension 2	Communalities (h^2)	Residual variance (u^2)
FCS	−0.17	0.69	0.54	0.455
HDDS	0.08	0.86	0.71	0.287
rCSI	0.48	−0.12	0.27	0.730
HHS	0.98	0.01	0.96	0.045
Model summary	Dimension 1	Dimension 2		
Sum of squared loadings	1.25	1.24		
Proportion of variance	0.31	0.31		
Proportion of explained variance	0.50	0.50		
Factor correlations	Dimension 1			
Dimension 2	−0.19			

The correlation between the latent dimensions is also weak; though we cannot objectively label what these factors represent, they clearly measure independent phenomena. If we accept that the four variables are all valid measures of food security, then each pair of indicators—HDDS/FCS and rCSI/HHS—appears to provide unique information about some unobservable dimension of food security. It is worth noting that this segregation of indicators holds despite the fact that HDDS and FCS measure food security outcomes on different time scales (24 h and one week, respectively), as do rCSI and HHS (one week and one month, respectively).

The results also indicate that the latent dimensions account for strongly differing proportions of the variance observed in each measurement variable. Dimension 1 and Dimension 2 together account for nearly all of the variance in HHS ($h^2 = 0.96$) but only a small fraction of the variance in rCSI ($h^2 = 0.27$). FCS ($h^2 = 0.54$) and HDDS ($h^2 = 0.71$) are intermediate cases. This may result from the fact that (1) other dimensions of food security not able to be extracted by the covariance structure of the four variables—that is, dimensions unique to (say) rCSI—are present; and/or (2) variables with low h^2 contain information about phenomena other than food security. Overall, we see that 62% of the total variance across all measurement variables is accounted for by the latent dimensions, with each dimension picking up half of this variance.

6. Discussion

We use a uniquely rich multi-country dataset to analyze the correlation structure of four commonly used indicators of food security, and to extract latent factors from this correlation structure. We find that several of these indicators are strongly associated (especially FCS-HDDS and rCSI-HHS), but many pairs are only weakly associated. All of these correlations are statistically significant, as expected given the size of the dataset. But equally importantly, given the weak correlation between several of these indicators, it is clear that all indicators cannot reliably be used interchangeably as indicators of the *same overall phenomenon* (i.e., "food security" broadly). While the strength of correlation varies among the original form of these indicators, these variables are more frequently used in categorical form—sometimes in a three-category form, as discussed in this paper, but sometimes as simple prevalence estimates that combine (most frequently) the "moderate" and "severe" categories. Figs. 2 and 4 disaggregate the results by individual data set, and depict the poorer concordance graphically. FA confirms what the continuous quantitative and categorical comparisons suggest: these four different indicators of "food security" are capturing two different underlying latent variables related to food security that are only weakly correlated to each other.

While it is not possible to specify exactly what these two latent variables are, we offer two interpretations based on our earlier discussion of the dimensions implicit in the World Food Summit definition of food security, as well as the theoretical work mentioned in the introduction and literature review. The first possibility follows a more standard interpretation of the indicators: Dimension 1, which correlates strongly with experiences of extreme food shortfall (HHS) or with behaviors that people rely on to cope with food shortfalls of a less extreme nature (rCSI), may represent the dimension of the *quantity* of food consumption; Dimension 2, which correlates with FCS and HDDS, can be interpreted to represent the dimension of the *diversity* of dietary intake. A second interpretation—suggested by an anonymous reviewer—would see Dimension 1 as representing the costs of constrained access to food, as reflected in coping behaviors (e.g., reducing size and number of meals, restricting consumption by adults) and extreme states of deprivation wherein options have been exhausted (e.g., going to bed hungry, going a full 24-h period without eating). Dimension 2 (FCS/HDDS), meanwhile, represents actual realized consumption: households are directly reporting consumption behaviors, the combined consequence of food availability and access. This distinction between costs of access and realized consumption is, in our view, a theoretically stronger interpretation than the standard quantity/quality categorization. Empirically, however, the only conclusion possible is that these two dimensions, whatever they may be, are not strongly correlated with each other.[4]

There are several implications to these findings. First, these results provide empirical support for the conceptual argument made by Coates (2013) with respect to food security and Ravallion (2011) in the realm of poverty measurement that multidimensional constructs should be captured through *a set of indicators* that validly represent the phenomenon's key dimensions, rather than through one summary indicator that obfuscates the contributions and implications of each dimension. The weak associations between the continuous forms of the variables and lack of categorical concordance suggest that these indicators are measuring different dimensions of food security; this makes clear that food security cannot be measured with a single scale, and these indicators should not be used as stand-alone measures of the overall concept of food security. Therefore, the implication for programmatic and policy application is that *more than one indicator should be used* to describe the food security status of a population, and that *using one indicator from each group* (i.e., one dietary diversity and one behavioral/experiential indicator) provides greater diagnostic understanding of which dimensions of food insecurity, or combinations of dimensions, are a problem for which groups of households.

Such a scheme is depicted using Table 2 below, which looks at the categorical relationship of rCSI and FCS from the pooled dataset. Only 41% of observations are concordant across the two indicators, and over 24% are discordant by more than one category. In this cross-tabulation, using the two indicators in combination identifies

[4] We note that correlation of these dimensions with income, expenditure, anthropometric, or other types of data may elucidate the nature of these dimensions; unfortunately, the collection of datasets used in this analysis were not selected based on the availability of standardized data regarding these phenomena, and so such an approach is not possible in the current work.

Table 2
rCSI-FCS Cross-Tabulations.

		FCS (%)			
		Acceptable	Borderline	Poor	Total
rCSI (%)	Food secure	30.4	8.3	2.8	41.6
	Moderately food insecure	15.4	3.5	1.0	19.9
	Severely food insecure	21.4	10.3	6.8	38.5
Total		67.2	22.2	10.7	100.0

Green High diversity; low coping	Yellow. Mixed results: intermediate category	Red. Low diversity; high coping

(cross-hatching indicates priority for further investigation)

over a quarter of households that are discordant by more than one category. Of these, 21.4% are classified as severely food insecure in terms of coping and acceptable in terms of diet diversity, while 3% are categorized as having poor diet diversity but report low coping according to the rCSI (top right and bottom left cells). Note, however, that these results are contingent on accepting the given category cut-offs for these indicators; other work suggests that interpretation of the categorical versions of these indicators is highly sensitive to the choice of cut-offs (Vaitla et al., 2015).

The low diversity-high coping category can clearly be identified as the highest risk group. But this approach also reveals two divergent groups of households that appear to be grappling with different aspects of food insecurity. The first might be representative of a high degree of reliance of unusual foods (a commonly mentioned coping strategy in a more complete CSI indicator) which increases diversity but not quantity; the second could indicate a population that is receiving food assistance—so getting an adequate amount to avoid high levels of coping, but not getting much diversity. Alternatively, the first group may be able to access food, but at considerable cost; the second might be struggling to obtain adequate food, but have not yet employed harmful coping strategies to deal with this constrained access. These results are suggestive of the need for interventions that are better tailored to challenges experienced by groups of households facing related, though different, manifestations of food insecurity.

Further research is required to test these conclusions. The current study has some limitations. While the data on which this study is based represents a global search for comparative datasets, there is a clear geographic bias. About two-thirds of the observations come from just six of the 21 datasets (Zimbabwe 2010 and 12, Kenya FSSG 12, Sudan BNSK 13, Ethiopia DFAP 12, and Somalia CVD 11). Sub-Saharan Africa provides nearly 72% of the data, with almost a quarter from Zimbabwe alone. Four relatively small datasets from Asia (three from Pakistan and one from Mongolia) and only three datasets from the Americas (all from Haiti) were used. The analysis here is largely based on pairwise comparisons, as that is all that most of the datasets allowed. Only a few datasets included three of the indicators, and only the Haiti datasets included all four of the indicators of interest in this study.

In addition, our analysis is complicated by uncertainty about key statistical properties of the indicators. Most importantly, we treat the indicators in the statistical analysis above as monotonic continuous variables, i.e., that all possible scores can be consistently ordered, an increasing score always implies unidirectional movement towards either food security or food insecurity, and the difference between scores is equivalent in any region of the scale (Cafiero et al., 2014). These assumptions are uncertain.[5]

Ultimately, a gold standard measure for each dimension of food security is required to resolve these issues and adequately evaluate the performance of associated indicators. For diversity and quantity, this would entail precise measurement of the quantity and type of food consumed over time by households, and subsequent comparison with nutrient needs in different contexts—an impracticable objective at the present moment. For other dimensions of food security, such as safety or cultural preferences, other gold standard metrics are needed. In the absence of such gold standards, this study suggests that using multiple indicators would help to increase the precision of food security measurement.

Appendix A

See Table A1.

[5] Consider a simple example in which one household consumed only staple grains (and no other food) seven days in the previous week, and another household consumed only pulses (and no other food) five days in the previous week and did not eat the remaining two days. Given the weighting scheme, the second household would have a higher FCS score (15) than the first household (14)—a potentially inaccurate conclusion in terms of overall food security or any single dimension of food security. In addition, it is not clear that the "difference" in food security between, say, a FCS of 15 and 14 is the same magnitude of food security difference that exists between FCS score 8 and 7, although treating the scale as continuous implies such equivalence. Similar uncertainties exist with rCSI and HDDS, and if these indicators indeed differ in their fundamental statistical properties, the analysis in the previous pages may produce biased results.

Table A1
Constituent items of FCS, HDDS, rCSI, and HHS.

Parent Indicator	Item Abbreviation	Item
FCS	F_STAPLE	In the past week, how many days has the household eaten any food made from grains, roots, or tubers?
	F_PULSE	In the past week, how many days has the household eaten any pulses?
	F_VEGET	In the past week, how many days has the household eaten any vegetables?
	F_FRUIT	In the past week, how many days has the household eaten any fruits?
	F_MEAT	In the past week, how many days has the household eaten any meat, fish, or eggs?
	F_DAIRY	In the past week, how many days has the household eaten any dairy products?
	F_SUGAR	In the past week, how many days has the household eaten any sugar, sugar products, or honey?
	F_OILFAT	In the past week, how many days has the household eaten any oils, fat, or butter?
HDDS	H_GRAIN	In the past 24 h, has the household eaten any [food made from local grains], bread, rice noodles, biscuits, or any other foods made from millet, sorghum, maize, rice, wheat, or [local grains]?
	H_TUBER	In the past 24 h, has the household eaten any potatoes, yams, manioc, cassava, or any other foods made from roots or tubers?
	H_VEGET	In the past 24 h, has the household eaten any vegetables?
	H_FRUIT	In the past 24 h, has the household eaten any fruits?
	H_MEAT	In the past 24 h, has the household eaten any beef, pork, lamb, goat, rabbit, wild game, chicken, duck, or any other birds, liver, kidney, heart, or other organ meats?
	H_EGGS	In the past 24 h, has the household eaten any eggs?
	H_FISH	In the past 24 h, has the household eaten any fresh or dried fish or shellfish?
	H_PULSE	In the past 24 h, has the household eaten any foods made from beans, peas, lentils, or nuts?
	H_DAIRY	In the past 24 h, has the household eaten any cheese, yogurt, milk, or other milk products?
	H_OILFAT	In the past 24 h, has the household eaten any oil, fat, or butter?
	H_SUGAR	In the past 24 h, has the household eaten any sugar or honey?
	H_MISC	In the past 24 h, has the household eaten any other foods, such as condiments, coffee, tea?
	RELY	In the past week, if there have been times when you did not have enough food or money to buy food, how many days has the HH had to rely on less preferred or less expensive food?
rCSI	BORROW	In the past week, if there have been times when you did not have enough food or money to buy food, how many days has the HH had to borrow food, or rely on help from a relative?
	LMTPOR	In the past week, if there have been times when you did not have enough food or money to buy food, how many days has the HH had to limit the size of portions at mealtime?
	ADLTRS	In the past week, if there have been times when you did not have enough food or money to buy food, how many days has the HH had to restrict consumption by adults in order to allow children to eat?
	FWMEAL	In the past week, if there have been times when you did not have enough food or money to buy food, how many days has the HH had to reduce the number of meals eaten in a day?
HHS	NOFOOD	In the past four weeks (30 days), was there ever no food to eat of any kind in your house because of lack of resources to get food?
	SLPHUN	In the past four weeks (30 days), did you or any household member go to sleep at night hungry because there was not enough food?
	NOEAT	In the past four weeks (30 days), did you or any HH member have to go a whole day and night without eating anything because there was not enough food?

Appendix B

See Fig. B1 and Tables B1–B3.

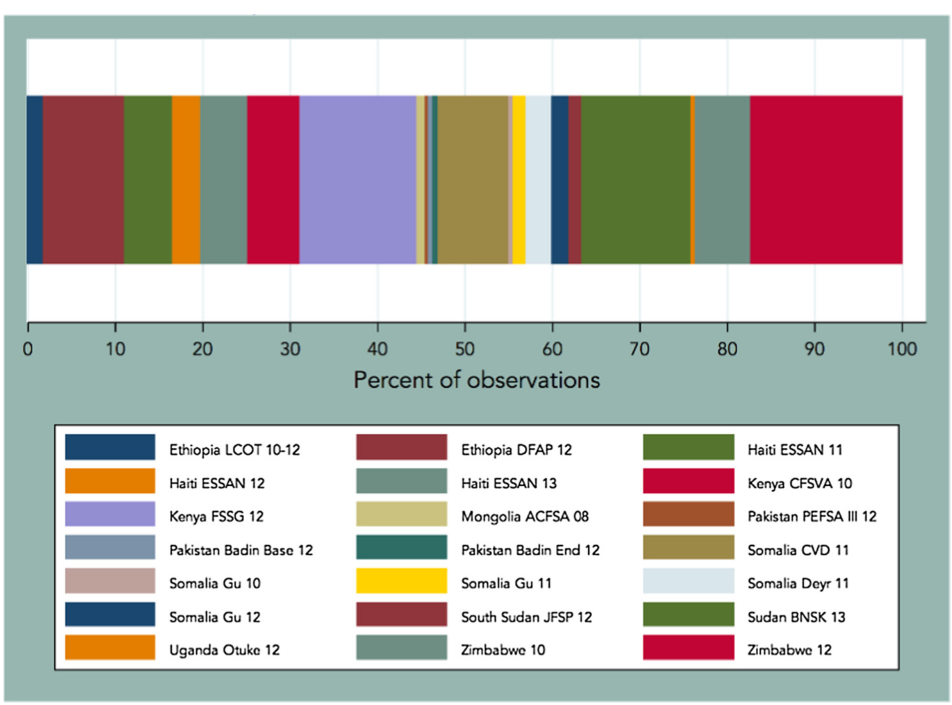

Fig. B1. Observations by dataset.

Table B1
Datasets used, number of observations per indicator, and percentage of observations for each indicator coming from a given dataset.

Country	Year	Dataset	Agency	FCS	HDDS	rCSI	HHS
Ethiopia[a]	2010–12	Livelihoods Change Over Time (LCOT)	Tufts University, Mekele University			1167 2.4%	1164 4.5%
	2012	Development Food Aid Project (DFAP)	Catholic Relief Services, Food for the Hungry, Relief Society of Tigray, Save the Children USA		6037 25.2%	5689 11.9%	5580 21.6%
Haiti	2011	L'enquête de suivi de la sécurité alimentaire et nutritionnel (ESSAN)	Coordination Nationale de la Securité Alimentaire (CNSA) and partners	3556 8.6%	3516 14.7%	3533 7.4%	3522 13.6%
	2012	ESSAN	CNSA and partners	2080 5.0%		2077 4.4%	2078 8.0%
	2013	ESSAN	CNSA and partners	3501 8.5%	3501 14.6%	3493 7.3%	3497 13.5%
Kenya	2010	Comprehensive Food Security and Vulnerability Analysis (CFSVA)	World Food Program (WFO)	3863 9.4%		3900 8.2%	
	2012	Food Security Steering Group (FSSG)	KFSSG	4929 11.9%		8051 16.9%	
Mongolia	2008	Aimag Center Food Security Assessment (ACFSA)	Mercy Corps		661 2.8%		659 2.5%
Pakistan	2012	Pakistan Emergency Food Security Alliance (PEFSA) III	Action Contre la Faim (ACF)	209 0.5%	210 0.9%	210 0.4%	
	2012	Emergency Nutrition, Food Security and Livelihoods Support to Flood-Affected Populations in Pakistan ("Badin") baseline	ACF		354 1.5%	171 0.4%	
	2012	Badin endline	ACF		362 1.5%		363 1.4%
Somalia	2011	Cash/voucher distribution baseline	UNICEF Cash Consortium		4531 18.9%		
	2010	*Gu* season nutrition assessment, internally displaced person (IDP) datasets	Food Security and Nutrition Analysis Unit (FSNAU)		350 1.5%	349 0.7%	
	2011	*Deyr* season nutrition assessment, IDP	FSNAU		973 4.1%	971 2.0%	
	2011	*Gu* season nutrition assessment, IDP	FSNAU		1310 5.5%	1074 2.3%	
	2012	*Deyr* season nutrition assessment, IDP	FSNAU		953 4.0%	739 1.6%	
South Sudan	2012	Jonglei Food Security Program (JFSP)	Catholic Relief Services		914 3.8%	910 1.9%	916 3.5%
Sudan	2013	Blue Nile and South Kordofan (BNSK) household survey	Food Security Monitoring Unit of BNSK	8122 19.7%			8084 31.3%
Uganda	2012	Otuke endline survey	ACF	324 0.8%	324 1.4%		
Zimbabwe	2010	Zimbabwe Vulnerability Assessment Committee (ZIMVAC)	ZIMVAC	3453 8.4%		4059 8.5%	
	2012	ZIMVAC	ZIMVAC	11,251 27.3%		11,250 23.6%	
Totals				**41,288**	**23,996**	**47,643**	**25,863**

Column (indicator) percentages shown.
[a] The LCOT dataset included four rounds of panel data between 2010 and 2012, and so was considered a single dataset. In contrast, the Haiti, Somalia FSNAU, and Zimbabwe datasets included multiple rounds of data from the same population, but are cross-sectional and are considered separate datasets.

Table B2
Description of datasets used.

Dataset/Year	Timing	Locality	Target Group
Ethiopia LCOT 10–12	Two lean season & two harvest season rounds (panel data)	Selected woredas of eastern Tigray region, northern Ethiopia	Various livelihood and wealth groups
Ethiopia DFAP 12	Lean season	Critically food insecure districts of Tigray, Oromiya, Amhara, and Somali regions	Households included in the DFAP; mix of highland and lowland agricultural agro-pastoral areas
Haiti ESSAN 11	Lean season	Nationwide	Representative sample, stratified by department and urban/rural residence
Haiti ESSAN 12	Harvest season	Nationwide	Representative sample, stratified by department and urban/rural residence
Haiti ESSAN 13	Harvest season	Nationwide	Representative sample, stratified by department and urban/rural residence
Kenya CFSVA 10	Urban focus; Ramadan taking place in some areas	Various high-density urban areas of Kenya	Urban households associated with nine livelihood clusters
Kenya FSSG 12	Varies by livelihood zone; some harvest season, some lean season	Sentinel sites in 9 livelihood zones, 2 refugee camps, and 4 HIV/AIDS project areas	Food security program beneficiary and non-beneficiary households within targeted communities
Mongolia ACFSA 08	Varies by location, generally the milder of the two annual lean seasons	Urban areas outside national capital	Representative samples of each urban center
Pakistan PEFSA III 12	Generally in lean season	Flood affected districts of Sindh province, SE Pakistan	Flood-affected beneficiary households of various PEFSA programs

(*continued on next page*)

Table B2 (*continued*)

Dataset/Year	Timing	Locality	Target Group
Pakistan Badin Base 12	Harvest season	Badin district, Sindh province	Flood-affected food security and livelihoods program beneficiary households
Pakistan Badin End 12	Harvest season	Badin district, Sindh province	Flood-affected food security and livelihoods program beneficiary households
Somalia CVD 11	Varies, as survey was conducted over a one-year period	9 regions of south central Somalia	Beneficiaries of cash/voucher interventions
Somalia Gu 10	Lean season, but focus on IDP population	Various IDP camps in northern Somalia	IDPs
Somalia Deyr 11	Lean season, but focus on IDP population	Various IDP camps in northern Somalia	IDPs
Somalia Gu 11	Lean season, but focus on IDP population	Various IDP camps in northern Somalia	IDPs
Somalia Deyr 12	Lean season, but focus on IDP population	Various IDP camps in northern Somalia	IDPs
South Sudan JFSP 12	Lean season	Jonglei state	Households in eight chronically and transitorily food insecure counties and one sub-county
Sudan BNSK 13	Varies depending on date of data collection; some lean season, some harvest season	South Kordofan and Blue Nile states	Mix of residents and displaced families; also stratified by wealth group
Uganda Otuke 12	Harvest season	Otuke district of Lango sub-region, northern Uganda	Participants of food security/livelihoods intervention in five sub-countries
Zimbabwe 10	Harvest season	Rural areas, nationwide	Representative samples of province and district levels
Zimbabwe 12	Harvest season	Rural areas, nationwide	Representative samples of province and district levels

Table B3
Number of pairwise datasets and observations.

Pair	Number of pairwise datasets	Number of pairwise observations
rCSI-FCS	8	32,649
rCSI-HDDS	10	16,844
rCSI-HHS	6	16,393
FCS-HDDS	4	7550
FCS-HHS	4	17,173
HDDS-HHS	6	14,460

Appendix C

See Table C1.

Table C1
Results of factor analysis using polychoric correlations.

Standardized loadings	Dimension 1	Dimension 2	Communalities (h^2)	Residual variance (u^2)
FCS	−0.17	0.71	0.60	0.40
HDDS	0.10	0.83	0.66	0.34
rCSI	0.48	−0.13	0.28	0.72
HHS	0.74	0.02	0.54	0.46
Model summary	**Dimension 1**	**Dimension 2**		
Sum of squared loadings	1.24	0.84		
Proportion of variance	0.31	0.21		
Proportion of explained variance	0.59	0.41		
Factor correlations	**Dimension 1**			
Dimension 2	−0.28			

Appendix D. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foodpol.2017.02.006.

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