Part 6.

Methodological issues on analysis of food security

Towards the measurement of household resilience to food insecurity: applying a model to Palestinian household data

Luca Alinovi, Erdgin Mane and Donato Romano[26]

ABSTRACT

Most of the current literature on food security focuses on the assessment of household vulnerability in food-insecure regions. The concept of vulnerability, by definition, is dynamic and forward-looking. However, almost all statistical methodologies applied until now have been static and unable to predict future events. The main reasons for this are both conceptual, such as the complexity (multidimensionality) of the concept of food security and the unpredictability of the many shocks that cause food insecurity, and empirical, such as the absence of longitudinal data over a sufficiently long period to enable the various sources of risk to express themselves, thereby not allowing the analysis of trends and risks.

For this reason, the concept of resilience has recently been introduced into food security literature. It aims to measure the capability of households to absorb the negative effects of unpredictable shocks or disasters, rather than predicting the occurrence of a crisis (as is the case in most vulnerability literature).

The definition of food system resilience directly affects the methodology adopted for its measurement. In the model described in this paper, household resilience is measured according to four building blocks: income and food access; assets; access to public services; and social safety nets. Stability and adaptive strategies are two additional dimensions that cut across these building blocks and account for households' capacity to respond and adapt to shocks.

In order to measure household resilience to food insecurity, an index was developed for each of these aspects, based on indicators from the Palestinian Public Perception Survey (PPSS). The process of building the indices involved the use of decision matrices and multivariate methods. The decision rules for building the indices were validated through classification and regression tree (CART) methodology to highlight the factors (indicators) that play a major role in qualifying the building blocks of household resilience. This information is crucial for policy-makers in general, and for food crisis response planning in particular.

INTRODUCTION

Most research in the field of food security has focused on developing and refining methods of analysis to predict the likelihood of a crisis more accurately. Such work has centred on the development of advanced early warning systems (EWS), using behavioural patterns in the economy to judge whether a crisis is about to happen, from the value change of selected indicators (Buchanan-Smith and Davies, 1995).

In the last decade, collaboration between the natural and social scientists concerned with the sustainability of jointly determined ecological-economic systems

---

[26] Agricultural Development Economics Division, FAO, Rome (first authors); and Department of Agricultural and Resource Economics, University of Florence, Italy.

has brought about a potentially fruitful concept, well-known in ecological literature but new as applied to socio-economic systems: the concept of resilience (Adger, 2000). Broadly speaking, resilience is a measure of a system's ability to withstand stresses and shocks, that is, its ability to persist in an uncertain world.

More recently, some scholars and practioneers (Folke, Berkes and Colding, 1998; Folke *et al*., 2002) and some international organizations, such as FAO (Hemrich and Alinovi, 2004), have proposed applying this concept to food security issues. The idea implicit to this is that this concept could complement the EWS approach. Indeed, the EWS approach tries to predict crisis, while the resilience framework tries to assess the current state of health of a food system, and hence its ability to withstand shocks should they occur.

Although this statement appears to be sound and promising, many steps must be taken before the implications of adopting the resilience approach are clear and it can be operationalized. For instance, there is the need to clarify the meaning and scope of resilience as applied to the analysis and management of food systems. There are many questions to be addressed in pursuing this objective: What is the meaning of resilience as applied to food systems? What is the relationship between resilience and other concepts, such as vulnerability? How should resilience in a food system be measured? etc.

This paper addresses only the last question in the specific context of households. The choice of this level of analysis is justified on the grounds that it is at this level that most risk management and risk coping strategies are implemented, especially in the case of informal strategies, which are those that are most available to the poor (cf. World Bank, 2001). Therefore, the paper does not analyse other important measurement issues that pertain to different levels of analysis (e.g., how to measure food system resilience at the regional, national or global level). Another limitation of this study is that, while acknowledging the genuinely dynamic nature of the resilience concept, it does not have access to the basic information required to capture and quantify the volatility and vulnerability over time that poor households say is so important. In order to do this, it would be necessary to have panel datasets that are long enough to monitor the same households over time, to allow for the direct observation of how households deal with shocks. Moreover, measuring household resilience to food insecurity requires data on household assets (physical, human and social capital), in combination with data on formal safety nets, the functioning of markets and the economic policies that determine a household's opportunity set and the range of activities it can pursue to manage risk. Many of today's household surveys do not provide such information. Last but not least, information on movement in and out of food security is informative only after the facts have occurred. The challenge is to find indicators that can monitor households' resilience before crisis occurs.

The objective of this paper is therefore to design a methodology for measuring households' resilience to food insecurity, and to discuss and highlight the data needs for monitoring that can eventually be adopted when suitable datasets become available. For the time being, it tests the proposed methodology using the data from the 11th Palestinian Public Perception Survey (PPSS 2007).

This paper has the following layout: the next (second) section summarizes the concept of resilience and its relationship to other relevant concepts in food security literature (e.g., vulnerability, sustainability). The third section presents the proposed model, the methodological approaches adopted for measuring household resilience and the dataset used to test the proposed method. The fourth and fifth sections describe the model's application to the case of Palestine and discuss the main results of the study. The sixth section focuses on model validation through CART. The conclusions summarize the main findings and discuss implications for future research and the design of statistical surveys.

RESILIENCE AND ITS RELATION TO HOUSEHOLD FOOD SECURITY

"A system is a group of interacting components, operating together for a common purpose, capable of reacting as a whole to external stimuli: it is affected directly by its own outputs and has a specified boundary based on the inclusion of all significant feedback." (Spedding, 1988: 18). A household can be thought of as the system within which the most important decisions affecting food security are made (e.g., what income-generating activities to engage in, how to allocate food and non-food consumption among household members, and what strategies to implement *ex-ante* and *ex-post* to manage and cope with risks).

The consequence of acknowledging this is important in terms of both analytical content (what is the subject of the analysis?) and methodology (how should this be analysed?). This implies that it is necessary to consider a household as a *complex adaptive system*. It also implies that the stability of the household as a complex system depends less on the stability of its individual components, than on the household's ability to maintain its self-organization in the face of stress and shock, in other words its *resilience*.

The concept of resilience, originally proposed in ecological literature (Holling, 1973) has recently been proposed for exploring the relative persistence of different states of nature in complex dynamic systems such as the socio-economic (Levin *et al*. 1998). Put simply, resilience is a measure of stability in the face of shocks to the system. Vulnerability is the flip side of resilience: when a system loses resilience it becomes vulnerable to change that previously could be absorbed (Kasperson and Kasperson, 2005). In a resilient system, change has the potential to create opportunity for development, novelty and innovation. In a vulnerable system, even small changes may be devastating. As resilience declines it takes a progressively smaller external event to cause a catastrophe. A social-ecological system with low resilience may still maintain its functions and generate resources and services - that is, it may seem to be in good shape - until it is subjected to disturbances and stochastic events, when it may exceed a critical threshold and change to a less desirable state.

Levin *et al*. (1998) argue that resilience offers a helpful way of thinking about the evolution of social systems, partly because it provides a means of analysing, measuring and implementing the sustainability of such systems. This is largely because resilience shifts attention away from long-term equilibrium, towards the system's capacity to respond to short-term shocks and stresses in a constructive and creative way. Diversity does not support stability, but it does support resilience and system functioning (Holling, 1973; 1986), while rigid control mechanisms that seek stability tend to erode resilience and facilitate the breakdown of the system. In fact, the multidimensionality of the food security concept and the complexity of the conduit mechanism to food insecurity, qualify the household as a complex system facing largely unpredictable exogenous shocks. For this reason, the concept of resilience as applied to household food security seems to be very promising: it aims to measure the capability of households to absorb the negative effects of unpredictable shocks or disasters, rather than predicting the occurrence of a crisis (as in the case of most vulnerability literature).

THE CONCEPTUAL MODEL AND METHODOLOGY

The model

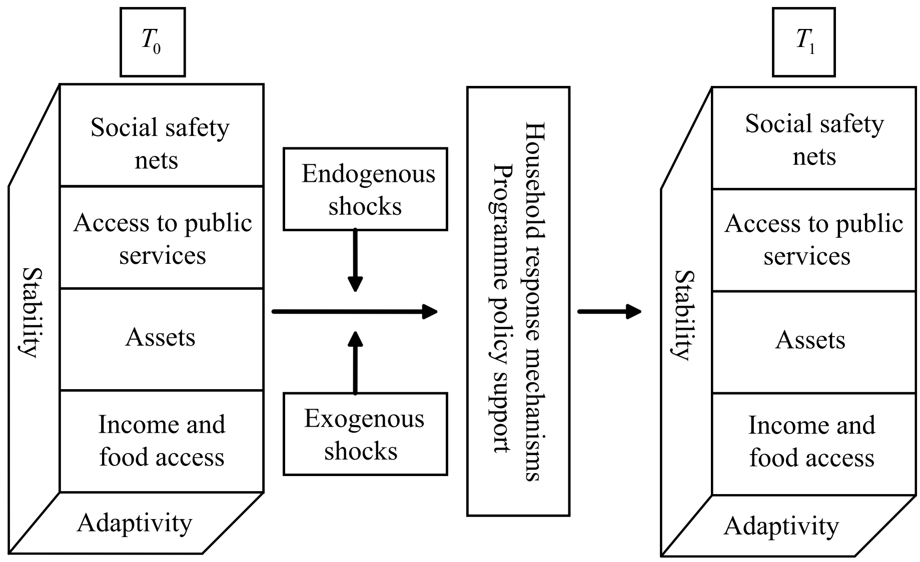
The conceptual framework shown in Figure 12.1 is the base for the resilience model. The idea is to estimate, at time T_0, every component separately and then generate a composite index of household resilience. Therefore, from T_0 to T_1, some shocks may occur. These shocks may be endogenous, if internally related to household capital, or exogenous, if externally related to household capital. The model assumes that the household has no control over exogenous shocks, but reacts to them by using available response mechanisms and through its absorption and adaptive capacities. Furthermore, a reaction to exogenous shocks (or systemic shocks) through policy support is undertaken by decision-makers other than the household (e.g., governments or international institutions), which might themselves be causes of external shocks. The different components of the resilience observed at time T_1 reflect how all these factors produce a change in the resilience of households.

The starting point in the methodological process is the 3D "parallelepiped" in Figure 12.1. In algebraic terms, the following equation estimates the resilience indicator for household *i*:

$$R_i = w_{IFA}IFA_i + w_{APS}APS_i + w_{SSN}SSN_i + w_S S_i + w_{AC}AC_i + w_A A_i + \varepsilon_i \qquad (1)$$

where: *R* = resilience; *S* = stability; *SSN* = social safety nets; *APS* = access to public services; *A* = assets; *IFA* = income and food access; *AC* = adaptive capacity; w_k = the weight for the *k*-th block in defining resilience; and ε_i = error term.

FIGURE 13.1.
Resilience-conceptual framework

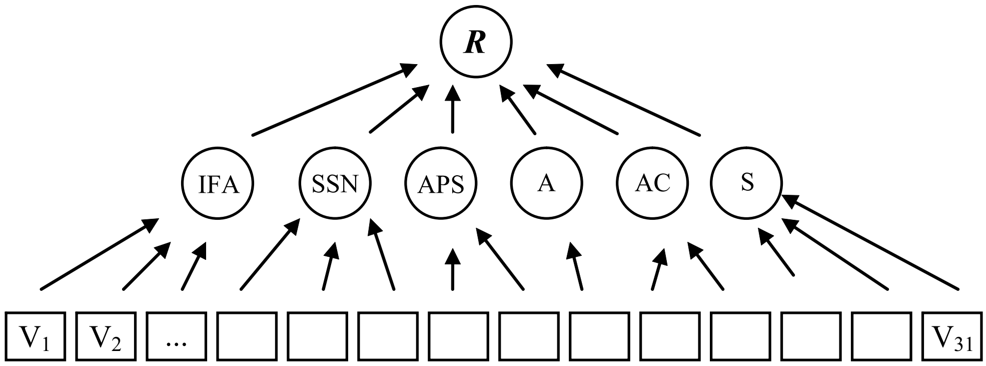


Resilience is a latent variable depending on the terms on the right hand side of Figure 13.1. Therefore, in order to estimate *R* there is need to estimate separately *IFA, S, SSN, APS, A* and *AC*, which are themselves latent variables. They are variables not directly observed in the survey, but it is possible to estimate them through multivariate techniques. For example, *IFA* is not just the income of the household, but also a series of estimated variables related to food consumption and expenditure and to households' perception of food access and dietary diversity, which are context and data-specific.

Methodological approaches

The model described in the previous section is an extension of multivariate regression models. In this case, it is a hierarchical model, where some of the variables are dependent on one side and independent from the other. Moreover, it also has to deal with unmeasured variables (latent). Figure 13.2 shows the path diagram of the model concerned.

FIGURE 13.2.
Path diagram of the household resilience model



In the causal models literature (Spirtes, Glymour and Scheines, 2000), the circles represent the latent variables and the boxes represent the observed variables. Most of the hierarchical or multi-level models studied in the literature deal with measured variables. In such cases, the regression properties are extended to the multi-level models. One of the innovations of this paper is its adoption of models for latent variables in complex survey data.

Considering the complexity of the model that is being dealt with, the following approaches can estimate household resilience.

Structural equation models (SEMs): These are the most appropriate tool for dealing with the kind of model described in the previous sub-section. Structural equation modelling combines factor analysis with regression. It is assumed that the set of measured variables is an imperfect measure of the underlying latent variable of interest. Structural equation modelling uses a factor analysis-type model to measure the latent variables via observed variables, simultaneously using a regression-type model for the relationship among the latent variables (Bollen, 1989). Generally, the estimation methods developed for SEMs are limited to the normally distributed observed variables, but in most cases (including in this paper), many variables are categorical or ordinal. Recent literature has proposed some attempts at broadening the SEM, but there are still difficulties regarding computational aspects (Muthén, 1984). It is also possible to use generalized latent variable models (Bartholomew and Knott, 1999; Skrondal and Rabe-Hesketh, 2004) to model different response types. A major concern in using SEM for measuring resilience is that the algorithms of SEM procedures are generally totally data-driven, while this paper includes some prior knowledge of the deterministic relations among measured variables. Therefore, Bayesian procedures could have been used for their flexibility, but owing to the quantity of variables to be used, the parameter identification problem requires careful consideration, in order to incorporate proper prior information. In the last decade, the use of Markov Chain Monte Carlo simulation methods (Arminger and Muthén, 1998; Lopes and West, 2003; Rowe, 2003; Mezzetti and Billari, 2005) has simplified the computational burden.

The multi-stage approach: This separately measures the latent variables through the observed variables. It involves the use of various sets of observed variables (represented as squares in Figure 12.2) to estimate the specific latent variables (circles in Figure 12.2). In other words, the circles in Figure 12.2 represent the common pattern in the underlying measured variables. The methods used for generating these latent variables depend on the measurement scales of the observed variables. The typology of the variables under each latent variable may be different, and it is necessary to use different methods for different types of variables. The methods commonly used for this kind of analysis are:

- SEMs;
- factorial analysis;
- principal components analysis;
- cluster analysis;
- Lisrel methods.

These methods are usually combined with deterministic decision matrices, which are based on prior knowledge of the variables. An auxiliary tool for data mining purposes is the classification and regression tree (CART) methodology, which can also be used for testing the validity of the adopted model.

In this paper, the second strategy for measuring resilience was adopted, for the following reasons: 1) the variables available are not all normally distributed, which may require the use of different multivariate techniques; and 2) measuring the different components separately makes the model more flexible, permitting the inclusion of prior information and solving the parameter identification problem.

The dataset

The Palestinian Public Perception Survey (PPPS) data is an interagency effort aimed at understanding socio-economic conditions in the West Bank and Gaza Strip. The University of Geneva implemented the 11th PPPS with the collaboration of several agencies, including FAO for the food security component; responsibility for data collection lay with the Palestinian Central Bureau of Statistics. PPPS provides a very rich dataset, including key indicators relevant for defining and analysing household food security status and its dynamics.

The data are repeated cross-sections, but it is not possible to use the surveys carried out before 2007 owing to changes made in the food security section of the questionnaire, which make the last survey incompatible with previous ones. The sample size was 2087 households, and the sampling design was a two-stage stratified cluster. There was adjustment of the sampling weights (the reciprocal of selection probability) to compensate for non-response and to satisfy the population size estimates, particularly in the disaggregated analysis by region, sex and age groups.

The questionnaire had the following sections:

- the roster, with the household's demographic, occupational and educational status;
- security/mobility;
- labour market;
- economic situation (including the food security module);
- assistance/assistance priorities;
- infrastructure;
- coping strategies;
- health;
- children/women;
- politics and peace/managing security;
- religion.

A first data screening took place during the preparatory phase of the analysis. The variables related to each component in equation (1) were then selected. The next section describes the process of variable selection and elaboration to obtain unique indicators.

APPLYING THE RESILIENCE MODEL TO THE PALESTINIAN DATA

The analytical framework follows a three-step procedure: 1) identification and processing of selected variables for each resilience block; 2) development of decision matrices and multi-variate methods (factor analysis, cluster analysis, principal components analysis, etc.) to build the indicator for each block; and 3) application of the CART methodology to build precise splitting rules based on the regression tree, for a better understanding of the whole process. The use of CART also allows the validation of the decision process and the identification of factors (indicators) that play a major role within the different blocks.

The variable selection procedures for generating the indicators for each building block are particularly complex in the resilience framework, where multidimensional correlations often make individual variables relevant to several blocks. The conceptual model described in the previous section simplified this issue.

Income and food access (IFA)

This indicator is directly related to the household's degree of access to food. The main food insecurity concern in Palestine (Mane, Alinovi and Sacco, 2007) is economic access to food. The traditional indicators of food access capacity are income and consumption, but nutritional indicators have also been included in this analysis. Generation of the IFA indicator involved the use of five indicators:

- average per person daily income (NIS/person/day);
- average per person daily consumption expenditure (food and non-food);
- average dietary energy consumption (DEC as kcal/person/day);
- household food insecurity access score (HFIAS);
- dietary diversity and food frequency score (DD).

PPPS directly measured the first two indicators. The other three were estimated by using specific methodologies. Estimation of the DEC used a FAO methodology (described in details in Sibrian, Ramasawmy and Mernies, 2006) permitting the transformation of food acquisition data into kilocalories per person per day at the household level. HFIAS is a scale of perception of household food insecurity and access, based on the nine questions developed by Food and Nutrition Technical Assistance (FANTA) (Coates, Swindale and Bilinsky, 2006). The utilization of 20 food groups permitted computation of the dietary diversity and food frequency score, which can also be used as a proxy indicator for food access (Hoddinott and Yohannes, 2002). Regression techniques imputed missing values.

All these indicators aim to measure food access. To generate the IFA indicator, a factor analysis was run, using the principal factor method and the scoring method suggested by Bartlett (1937). This method produces unbiased factors, but these may be less accurate than those produced by the regression method suggested by Thomson (1951). The regression-scored factors have the smallest mean square error but it is possible that the true factors contain bias. The factor produced is quite meaningful and it is possible to consider it the underlying latent variable for food access. Table 13.1 shows the eigen-values for each factor, while Table 13.2 shows the factor loading for the original variables. This involves the high correlation of income, consumption and DEC with the IFA indicators, but even the DD and HFIAS have a meaningful correlation. HFIAS has a negative correlation because it increases as food security decreases.

TABLE 13.1
Eigen values

Factor	Eigen-value
Factor 1	1.82865
Factor 2	0.18174
Factor 3	-0.10394
Factor 4	-0.11670
Factor 5	-0.21905

TABLE 13.2
Factor loadings and correlations

Variable	Factor 1	IFA
Income	0.7568	0.8789
Consumption	0.6760	0.7839
DD	0.4082	0.4410
HFIAS	-0.3530	-0.3793
DEC	0.7125	0.8279

Access to public services (APS)

Access to public services is strictly related to the assets available at the household level and their functions. Poor access to public services affects the capacity of the household to manage risks and respond to a crisis. The public services considered in the analysis are:

- health: physical access and quality of the service;
- quality of the education system;
- perception of security;
- mobility and transport limitations;
- water, electricity and telecommunications networks.

Regarding health, measurement involved two indicators: *physical access* to health (need not received, received after or within time limit) and the health care *quality score* (based on the quality of services provided in different health areas). An additional indicator on the *quality of the education system* (on an ordinal scale of one to six) was also measured. A proxy index based on the general *perception of security* was constructed (on an ordinal scale of one to four). Various sources generated an indicator based on restrictions to mobility, and this was measured by using different questions in the questionnaire (on an ordinal scale of one to three). Finally, an indicator of the number of available services providing water, electricity and telecommunications was developed.

Spatial distribution is a key factor for access to public services. It cannot be assumed that the relevance of different services is constant among different regions. For this reason, different factor analyses were run for the five sub-regions: North West Bank, Middle West Bank, East Jerusalem (considered separately because it has different socio-economic characteristics from those of the rest of Middle West Bank), South West Bank, and Gaza Strip. Table 13.3 shows the scoring coefficients of the Bartlett method for each subregion. The missing values for this block were imputed using the mean at governorate level.

TABLE 13.3
Bartlett's scoring coefficients

	North WB	Middle WB	Jerusalem	South WB	Gaza Strip
Health, physical access	0.69948	0.83512	0.18661	0.4269	0.27528
Health, quality	0.71387	0.82941	0.33513	0.63329	-0.19755
Educational system	0.14309	0.31666	-0.02624	0.34521	0.26809
Security perception	0.50444	0.26072	0.30694	0.44549	0.71213
Mobility constraints	0.56666	0.14465	0.58338	0.31384	0.74085
Water, electricity, etc.	0.09623	0.15815	-0.07116	0.35888	-0.45009

Social safety nets (SSN)

Social safety nets are a crucial aspect in the mitigation of crises in Palestine. More and more households are becoming dependent on assistance from international agencies, charities and NGOs. Help received from friends and relatives is also substantial. Therefore, safety nets can be considered as the capacity of the system to mitigate shocks, and as a general indicator to be included in the estimation of resilience. The variables used for generation of the SSN indicator are:

- amount of cash and in-kind assistance (continuous variable in NIS/person/day);
- quality of assistance (ordinal scale of one to four);
- job assistance (binary response, yes/no);
- monetary value of first and second types of assistance (continuous variable in NIS/person/day);
- evaluation of the main type of assistance (ordinal scale of one to four);
- frequency of assistance (count, quantity of received assistance in the last six months);
- overall opinion on targeting (categorical; assistance targeted to the needy; including some not needy; and targeted without distinction).

In this case too, missing values were treated using the mean at governorate level. Different multivariate exploratory techniques (PCA, FA and CA) were used to find the common patterns in the data, but the different tools could not perform well, owing to the presence of non-normally distributed variables. For example, the scoring coefficients in the factor analysis underestimated the categorical variables. The final SSN indicator was generated using a weighted sum of the variables listed above. The equation used was:[27]

$$SSN = (stdSSN\_1 + 2*stdSSN\_2 + 2*stdSSN\_3 + stdSSN\_4 + 2*stdSSN\_5 + 0.5*stdSSN\_6 + + 0.5*stdSSN\_7)/9$$

Assets (A)

Assets are part of household capital, and their availability is an important coping mechanism during periods of hardship. They therefore have to be considered as a key factor in estimating resilience. Information on assets was not available in the PPPS dataset, and so it was decided not to use proxies so as not to contaminate the estimates.

Adaptive capacity (AC)

The adaptive capacity indicates the capacity of a household to cope and adapt after a shock, enabling it to continue performing its own key functions. In other words, adaptive capacity provides the household with the capacity to absorb the shock. Having more coping strategies means having more probability of mitigating food insecurity after losing a job, for example. The characteristic of adaptability is the buffer effect for the household's key functions. The indicators used to measure adaptive capacity are:

- diversity of income sources (count, one to five);
- coping strategy index (quantitative, one to 16);
- capacity to keep up with food security in the future (ordinal scale of one to five);
- number of assistance sources (count, one to six).

The first variable indicates the number of *income sources from different sectors* (public, private, etc.); during a crisis, the more sources of income the household has, the less it is exposed to the risk of losing its income. The coping strategy index represents the number of available coping strategies that have not yet been used.

It was necessary to use a specific weight for the variable, *number of assistance sources*. It was difficult to apply the factor analysis correctly to this variable for the entire sample because the variable was particularly relevant only for the poorer households. The

[27] Where "std" indicates the standardized value of the relevant variable.

arbitrary weight adopted for AC_4 was included in the following equation, maintaining constant the proportions among the factor loadings of the other variables:

$$AC = (stdAC\_1 + 2*stdAC\_2 + 2*stdAC\_3 + 0.5*stdAC\_4)/5.5$$

Stability (S)

Stability is a widely used concept in food security literature, although it is usually used to describe the stability of food supply. In this paper, it is considered as a cross-sectoral dimension of resilience. An index of income stability, for instance, may be its variability (increase, decrease or none) in the last six months. The variables used for the measurement of stability are:

- professional skills (continuous);
- educational level (continuous);
- employment ratio (ratio, zero to one);
- number of household members to have lost their jobs (continuous);
- income stability (ordinal: increased, the same, decreased);
- assistance dependency (ratio, zero to one);
- assistance stability (ordinal: increased, the same, decreased);
- health stability (count, zero to eight);
- education system stability (ordinal: increased, the same, decreased).

In this case, given the multidimensionality of the feature, no prior decisions were taken. A factor analysis was run to analyse the correlation matrix using the iterated principal factor method. This method re-estimated the communalities iteratively. Then, the Bartlett method was used to generate the S indicator. Table 13.4 shows the correlation coefficients of the S indicator with the original variables.

TABLE 13.4
Correlation matrix

	S1	S2	S3	S4	S5	S6	S7	S8	S9
Stability	0.7384	0.8378	0.6505	-0.0549	0.0993	-0.35	0.2733	0.1196	-0.025

Estimation of resilience (R)

So far, this paper has looked at the first stage of the analysis, but it is necessary to fit all the pieces of the puzzle together to estimate resilience. In other words, the indicators estimated in the previous paragraphs become covariates in the estimation of resilience. Recalling equation (1):

$$R_i = w_{IFA}\hat{IFA} + w_{APS}\hat{APS}_i + w_{SSN}\hat{SSN}_i + w_S\hat{S}_i + w_{AC}\hat{AC}_i + \varepsilon_i$$

For exploratory purposes, a factor analysis was run using the iterated principal factor method. Table 13.5 shows the eigen values, which indicate that the first two factors are relevant, and Table 13.6 shows the factor loadings for the first two factors.

TABLE 13.5
Eigen values

	Eigen-value
Factor 1	1.19054
Factor 2	0.334
Factor 3	0.1423
Factor 4	0.04417
Factor 5	-0.00019

TABLE 13.6
Factor loadings

	Factor 1	Factor 2
IFA	0.6028	-0.0564
AC	0.5485	0.2593
S	0.687	-0.2487
APS	0.2331	0.2688
SSN	0.0019	0.3599

Table 13.6 shows that factor one does not capture information regarding social safety nets, but factor two does. For this reason, approximated weights were used, to account for both factors. Finally, the following equation measured the resilience indicator:

$$R = (2*stdIFA + stdAPS + stdAC + stdS + 0.5*stdSSN)/5.5$$

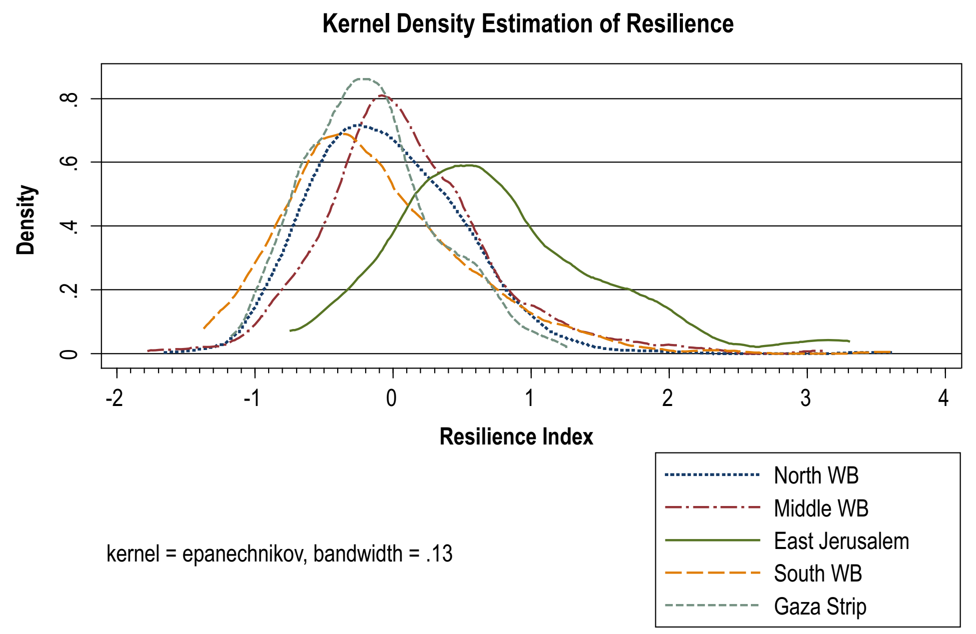
The coefficients used in the measurement of resilience are approximately proportional to the sum of the factor loadings in Table 12.6. The coefficient two for the standardized IFA represented the only difference. This was to place greater emphasis on household capital to make up for the lack of information on assets. The next section describes and discusses the results of these estimates.

DISCUSSION OF RESULTS

This section presents some of the estimates of the resilience index and its components in the five subregions of Palestine. Figure 13.3 shows the Epanechnikov's kernel density estimates of the resilience distribution. Presentation of the results involved the use of the non-parametric method owing to its major informative capacity.

Figure 13.3 shows the gap between East Jerusalem[28] and other regions. At first glance, it looks as though the other regions have more or less the same resilience level, so in this case the non-parametric approach is not very helpful. To obtain the significance level of the difference, a return to the parametric approach is required. Table 13.7 shows the means and standard deviations for resilience and its standardized components. The matrix in Table 13.8 shows the t-statistics for the pair comparison between the means of the different regions.

FIGURE 13.3.
The distribution of resilience in the five Palestinian subregions



[28] Jerusalem villages outside the wall are excluded. They are included in Middle West Bank.

TABLE 13.7
Means and standard deviations for resilience and its components

		Resilience		IFA		APS		SSN		AC		S	
Regions	**N**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
North WB	648	-0.041	0.545	-0.131	0.760	-0.125	0.950	-0.044	1.116	0.083	0.999	0.098	0.941
Middle WB	614	0.101	0.617	0.214	1.033	0.136	0.927	0.095	0.761	0.051	1.030	-0.108	0.987
Jerusalem	93	0.746	0.797	1.767	1.511	0.081	0.882	-0.358	0.597	0.164	1.115	0.503	1.297
South WB	408	-0.127	0.670	-0.136	0.937	0.113	0.899	-0.319	0.973	-0.346	0.912	-0.034	1.092
Gaza Strip	324	-0.162	0.470	-0.480	0.498	-0.172	1.290	0.412	1.100	0.126	0.921	-0.092	0.854
Total	**2 087**	**0**	**0.624**	**0**	**1**	**0**	**1**	**0**	**1**	**0**	**1**	**0**	**1**

TABLE 13.8
Matrix of t-statistics for the comparison of means

	North WB	Middle WB	Jerusalem	South WB	Gaza Strip
North WB	0				
Middle WB	-4.3462	0			
Jerusalem	-12.1941	-9.0115	0		
South WB	2.2779*	5.5916	10.9327	0	
Gaza Strip	3.4148	6.7209	13.805	0.8034**	0

* Pr(T < t) = 0.9885: not significant at 99 percent, but significant at 95 percent.

** Pr(T < t) = 0.7890: not significant.

The differences among regional resilience levels are all significant except for that between the Gaza Strip and South West Bank. This is owing to the high level of social safety nets in the Gaza Strip. Gaza has the highest amount of assistance from relatives and friends, but it also has the highest level of dependency on external assistance. Jerusalem has the highest values for R, IFA, AC, S, but also the highest level of inequality because it has the highest standard deviation.

MODEL VALIDATION WITH CART

CART was applied to test the process used for estimating the resilience indicator, based on the concept that sets of different variables and indicators belonging to different dimensions of food insecurity, the social sector and public services, are strictly correlated to the overall resilience indicator. For this reason, validation procedures are necessary to improve understanding of the relation between resilience and original variables, using the CART methodology (Steinberg and Colla, 1995; Breiman *et al.*, 1984). Such tools also allow the resilience decision tree and related splitting rules to be built, which is very important for gaining an understanding of the key determinants of resilience. The greatest advantage of CART is its cross-validation procedures, which allow measurement of the errors in the model. Other advantages of using CART are:

- robustness as a non-parametric tool;
- capacity to handle complex data structures;
- no requirement for PDF assumptions;
- overtaking of heteroskedasticity and multicollinearity;
- greater accuracy of testing procedures;
- capacity to deal with missing values;
- transferability of decision rules to new observations.

The target variable for the model implemented with CART was the resilience indicator. As this is a continuous variable, CART performed a *regression tree* (when the target variable is categorical, CART performs a *classification tree*). The model included, as predictors, all the original variables used in the empirical approach. The weights deriving from the sample design were also considered.

FIGURE 13.4.
The upper part of the regression tree

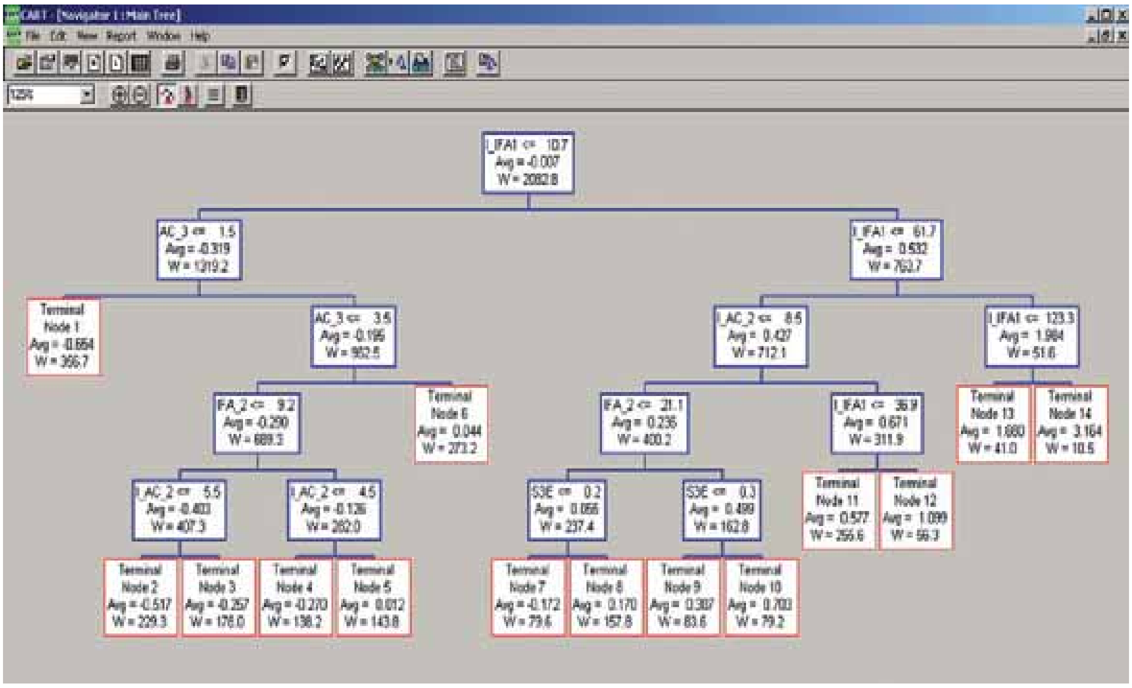


Figure 13.4 above illustrates the upper part of the regression tree generated by CART. The optimal tree has 141 terminal nodes, which has a relative cost (error) equal to 0.245. It is possible to calculate the approximated R-squared using the formula: (1- resubstitution error), that is, 1- 0.067 = 0.933. In fact, by running an OLS regression of the resilience index on the 31 original variables, the R-squared becomes 0.9825. The CART procedure included the use of the Gini splitting criterion and the tenfold cross-validation[29] for testing. Figure 13.4 shows the splitting rules, the mean of resilience and the weighted number of observations at each node.

The ranking of the variable importance shown in Table 13.9 explains the role of each variable in the definition of resilience. This ranking was measured considering the main splitters, competitors and surrogates.[30]

[29] The cross-validation test took place over ten sub-samples from the learning sample.

[30] When a variable is considered as a competitor, CART finds the best split that reduces node heterogeneity, whereas when the variable is considered as a surrogate, it is constrained to mimic the primary split.

TABLE 13.9
Variable importance

Code	Description	Importance	Code	Description	Importance
I_IFA1	Income	100	APS_4	Perception of security	2.57
IFA_2	Consumption	76.65	APS_5	Mobility constraints	2.13
I_IFA7	DEC	66.99	S6	Assistance dependency	1.75
I_AC_2	Coping strategies	50.37	SSN_4	Monetary value of 1st and 2nd type	1.65
I_IFA6	HFIAS	49.39	AC_1	Diversity of income sources	1.52
S3E	Employment ratio	46.79	S8	Health stability	1.40
AC_3	Capacity to keep up in the future	19.27	S9	Educational system stability	1.33
S2	Education level	7.46	S5	Income stability	1.24
APS_2	Health service quality	6.82	AC_4	No. of assistance sources	1.21
I_IFA5	Dietary diversity	6.44	SSN_6	Frequency of assistance	0.83
SSN_2	Quality of assistance	4.95	SSN_7	Opinion on targeting	0.61
SSN_5	Evaluation main assistance	4.23	APS_7	Water, electricity and telecommunications	0.61
SSN_1	Cash and in-kind assistance	3.74	S4	No. household members lost work	0.45
S1W	Professional skills	3.22	SSN_3	Employment assistance	0.13
APS_1	Physical access to health	2.95	S7	Assistance stability	0.05
APS_3	Education system	2.83			

Summing up, the main advantage of CART is its capacity to capture variables relevant for specific sub-groups of the population, which an OLS regression does not consider relevant for the whole population.

CONCLUSIONS

The analysis conducted on PPPS 2005 seems to confirm the validity of the conceptual framework adopted. The results are meaningful and the resilience index in the five subregions has significant differences. The same applies to the five components of the resilience model.

However, there were constraints on the analysis owing to the static nature of the available database. Therefore, in the future, it is necessary to carry out this analysis with panel data as soon as an appropriate database becomes available. It would also be interesting to extend the analysis to other key studies in order to assess the robustness of the proposed analytical framework as well as any emerging patterns of resilience.

Even though the methodology adopted gave significant results, it is necessary to test the other methodology proposed in this paper, that is, the structural equation modelling with Bayesian networks, before making a final decision on the most appropriate methodology.

Further work is also necessary on how to use the resilience index for identifying the key determinants needed to design adequate responses and policies to food insecurity, as well as for strengthening the economic resilience of households in crisis situations.

REFERENCES

Adger, N.W. 2000. Social and ecological resilience: are they related? *Progress in Human Geography*, 24(3): 347-364.

Arminger, G. & Muthén, B.O. 1998. A Bayesian approach to nonlinear latent variable models using Gibbs sampler and Metropolis-Hastings algorithm. *Psychometrika*, 63: 271-300.

Bartholomew, D.J. & Knott M. 1999. *Latent variable models and factor analysis*. London, Arnold.

Bartlett, M.S. 1937. The statistical conception of mental factors. *British Journal of Psychology,* 28: 97-104.

Bollen, K.A. 1989. *Structural equations with latent variables*. New York, Wiley and Sons.

Breiman, L., Friedman, J., Olshen, R. & Stone, C. 1984. *Classification and regression trees*. Pacific Grove, Wadsworth.

Buchanan-Smith, M. & Davies, S. 1995. *Famine early warning and response: The missing links?* London, ITDG.

Coates, J., Swindale, A. & Bilinsky, P. 2006. *Household food insecurity access scale (HFIAS) for measurement of food access: indicator guide*. Washington, DC, United States Agency for International Development (USAID) Food and Nutrition Technical Assistance Project (FANTA).

Folke, C., Berkes, F. & Colding, J. 1998. Ecological practices and social mechanism for building resilience and sustainability. *In* F. Berkes and C. Folke. *Linking social and ecological systems,* pp. 414-436. Cambridge, UK, Cambridge University Press.

Folke, C., Carpenter S., Elmqvist, T., Gunderson, L., Holling, C.S. & Walker, B. 2002. Resilience and sustainable development: building adaptive capacity in a world of transformations. *Ambio,* 31(5): 437-440.

Hemrich, G. & Alinovi, L. 2004. Factoring food systems' resilience in the response to protracted crisis. *In* FAO. *The state of food insecurity in the world 2004*. Rome, FAO.

Hoddinott, J. & Yohannes, Y. 2002. *Dietary diversity as a household food security indicator*.

Washington, DC, Food and Nutrition Technical Assistance Project, Academy for Educational Development.

Holling, C.S. 1973. Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics,* 4: 1-23.

Holling, C.S. 1986. Resilience of ecosystems; local surprise and global change. *In* W.C. Clark and R.E. Munn, eds. *Sustainable development of the biosphere,* pp. 292-317. Cambridge, UK, Cambridge University Press.

Kasperson, J.X. & Kasperson, R.E. 2005. *The social contours of risk*. London, Earthscan.

Levin, S.A. *et al*. 1998. Resilience in natural and socioeconomic systems. *Environment and Development Economics,* 3(2): 222-235.

Lopes, H. & West, M. 2003. Bayesian model assessment in factor analysis. *Statistica Sinica*, 14: 41-67.

Mane, E., Alinovi, L. & Sacco, E. 2007. Profiling food security in Palestinian governorates: Some classification techniques based on household-level data. Paper presented at the International Conference on Statistics and Development, Ramallah, 27-28 March 2007.

Mezzetti, M. & Billari, F.C. 2005. Bayesian correlated factor analysis of socio-demographic indicators. *Statistical Methods and Application,* 14: 223-241.

Muthén, B.O. 1984. A general structural equation model with dichotomous, ordered categorical and continuous latent indicators. *Psychometrika,* 49: 115-132.

Pingali, P., Alinovi, L. & Sutton, J. 2005. Food security in complex emergencies: enhancing food system resilience. *Disasters,* 29(Supp. 1): S5-S24.

Rowe, D.B. 2003*. Multivariate Bayesian statistics: models for source separation and signal unmixing.* Boca Raton, Florida, USA, CRC Press.

Sibrián, R., Ramasawmy, S. & Mernies, J. 2006. *Measuring hunger at sub-national level: The FAO approach applied to household survey data.* ESS/ESSA/005 FAO Working Papers. Rome, FAO.

Skrondal, A. & Rabe-Hesketh, S. 2004. *Generalized latent variable modelling: multilevel,*
longitudinal, and structural equation models. Boca Raton, Florida, USA, Chapman and Hall/CRC.

Spedding, C.R.W. 1988. *An introduction to agricultural systems*, second edition. Barking, UK, Elsevier.

Spirtes, P., Glymour, C. & Scheines, R. 2000. *Causation, prediction and search.* Cambridge, Massachusetts, USA, MIT Press.

Steinberg, D. & Colla, P. 1995. *CART: tree-structured non-parametric data analysis*. San Diego, California, USA, Salford Systems.

Thomson, G.H. 1951. *The factorial analysis of human ability*. London, University of London Press.

World Bank. 2001. *World development report 2000/01. Attacking poverty*. New York, Oxford University Press.

Indicators on food deprivation and income deprivation at national and sub-national levels: methodological issues

Ricardo Sibrián[31]

ABSTRACT

Indicators to measure income and food deprivation are useful for understanding food insecurity at national level and within countries. This paper discusses two indicators: prevalence of food deprivation (undernourishment), and prevalence of critical food poverty. Both indicators are based on nutritional underlying criteria, which are also derived from food consumption and income data collected in household surveys. Prevalence of food deprivation is Millennium Development Goal (MDG) indicator number 5, which uses the distribution of energy consumption as a base; prevalence of critical food poverty is a new indicator that links food deprivation to income deprivation, based on the distribution of income.

The link is the concept of minimum dietary energy requirement (MDER) used in the FAO methodology as the cut-off value in the distribution of energy consumption for estimating undernourishment. The critical food poverty line for estimating the prevalence of critical food poverty is the cost of the MDER, based on energy-yielding nutrient prices for a macronutrient-balanced diet accessible to low-income population groups. The macronutrient-balanced diet uses the recommendations of a Joint WHO/FAO Expert Consultation on Diet, Nutrition and the Prevention of Chronic Diseases (2002, Geneva) as its point of reference. The following examples illustrate the results of both indicators for a sample of countries in different continents.

Key words: food poverty, undernourishment, food insecurity, food security

Acknowledgements: the European Community for financial support.

BACKGROUND

FAO has been monitoring food deprivation continuously on request since the 1996 World Food Summit (WFS) and the 2000 Millennium Declaration. The MDG target on hunger reduction refers to reduction in the proportion of the population suffering from food deprivation; the WFS target refers to reduction in the number of people suffering from food deprivation. The WFS target is more challenging than the MDG target. Reducing the number of food-deprived people implies reducing the proportion of food deprivation, while halving the proportion of food deprivation does not necessarily imply reducing the number of hungry people.

In 2002, FAO convened the International Scientific Symposium (ISS) on Measurement and Assessment of Food Deprivation and Undernutrition. ISS reviewed the methodologies currently available for monitoring food deprivation and undernutrition. ISS recognized that food insecurity is a multifaceted and complex phenomenon, and no perfect single measure captures all aspects. It also recommended the use of a suite of indicators to understand determinants of food insecurity, such as food availability, access and utilization, as well as vulnerability. All these dimensions

[31] Statistics Division, FAO, Rome.

are interrelated by reciprocal causal or associative links, and a suite of indicators may help to give an understanding of why people are food insecure and may help improve the targeting and design of informed policies and actions.

For this purpose, FAO Statistics Division has developed statistical procedures for estimating a suite of food security statistics using the Food Security Statistics Module (FSSM) software. FSSM produces many food security statistics at national and sub-national levels using food consumption and income data collected in national household surveys (NHS), including the prevalence of food deprivation and the number of undernourished in total population. It is the use of these two indicators that allows the monitoring of the MDG and WFS targets on food deprivation (hunger) reduction.

The statistical procedures in FSSM include new expert recommendations on energy requirements, as well as statistics derived from a Technical Expert Workshop on Energy Requirements for Estimating Food Deprivation and Food Excess (January 2005, Rome). FSSM also includes a recently published report of a Joint FAO/World Health Organization (WHO)/United Nations University (UNU) Expert Consultation on Human Energy Requirements (FAO, 2004), for calculating the minimum energy requirements to estimate the prevalence of food deprivation.

OBJECTIVES

The main objective of this paper is to examine the indicators used for measuring food deprivation (hunger), including those used for monitoring the WFS and MDG targets, as well as a new indicator on income deprivation (critical food poverty). These indicators are the prevalence of food deprivation (undernourishment) in the total population (i.e., consuming insufficient food to meet minimum energy requirements) and the prevalence of critical food poverty (i.e., lacking income to acquire food to meet the minimum energy requirements). Both indicators use the same nutritional underlying criteria and are derived from food consumption and income data collected in household surveys.

METHODOLOGICAL ISSUES

In estimating the prevalence of food deprivation and critical food poverty, there are several methodological issues concerning the use of the underlying theoretical distribution for both dietary energy consumption (DEC) and income or proxy total expenditure. This section focuses on the statistical framework for both food deprivation and income deprivation indicators.

Statistical framework for estimating food deprivation

Prevalence of food deprivation is the proportion of the population below the minimum dietary energy consumption (MDER).

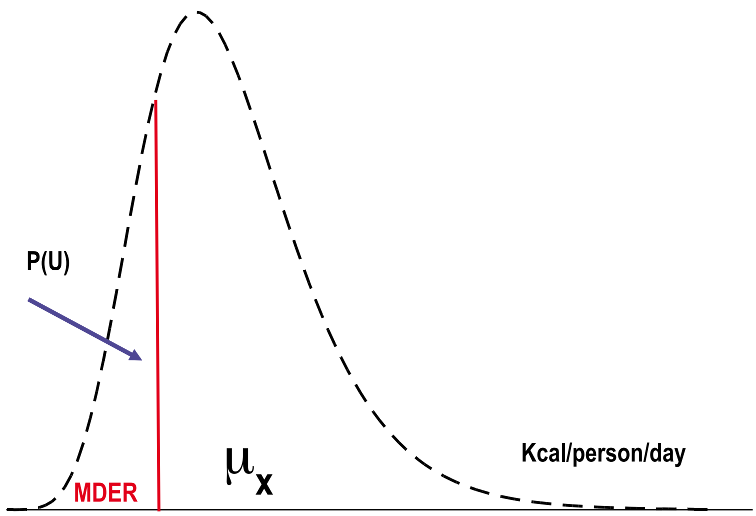
The probability distribution framework is defined as follows:

$$P(U) = P(X < MDER) = \int_{x<MDER} f_x(x)dx = F_x(MDER)$$

where *P(U)* is the proportion of food deprivation in total population; *(x)* is DEC (kcal/person/day); *MDER* is a cut-off point reflecting the minimum acceptable level of energy consumption (kcal/person/day); *f(x)* is the density function of energy consumption depicted on the right hand side of Figure 14.1; and *Fx* is the corresponding cumulative distribution function of DEC.

The curve f(x) in Figure 14.1. depicts the proportion of the population corresponding to the different per person DEC levels (x) represented by the horizontal line. The area under the curve up to MDER represents the proportion of the population consuming insufficient food to meet the minimum energy requirement, P(U). Estimation of the prevalence of food deprivation involves the use of several approaches, P(U). The following paragraphs describe the most commonly used.

FIGURE 14.1.
Probability distribution framework for estimating food deprivation



The first approach is the adequacy of energy consumption, which is the ratio of energy consumption to energy requirement, expressed as a percentage. This is also of use in estimating inadequacy of macronutrient consumption, such as protein, and micronutrients, such as vitamin A. This indicator depends on the following: if the household DEC adequacy is less than 70 percent, for example, all household members are in the category of food-deprived in terms of dietary energy. The prevalence of food deprivation in total population is therefore the number of members of households falling into this category divided by the number of members in all sampled households and expressed as a percentage. Although this approach has been used less since the mid-1980s, because it does not take into consideration the distribution of energy consumption within the population - that is, the inequality in access to food - many practitioners still use it for the purpose of food insecurity assessments. The 70 percent inadequacy cut-off value, which is an implied MDER, yields the same prevalence of food deprivation in different populations with the same average energy consumption but different inequalities in the distribution of that energy consumption.

The second approach, recently proposed by Smith, Alderman and Aduayom (2006) from the International Food Policy and Research Institute (IFPRI), is a direct comparison of the household energy consumption of each sampled household in an NHS with the household energy requirement. The latter derives from the sum of the energy requirements of all members in the household for light physical activity, based on their median reference body weights in the WHO growth standards corresponding to their sexes and ages. Any household with a total energy consumption below the respective total energy requirement is classified as undernourished. The prevalence of food deprivation in the population is the total number of individuals in the households classified as food-deprived divided by the total number of individuals in all the sampled households.

This approach takes into consideration the inequality in access to energy consumption within a population. Unfortunately, however, the approach also has several flaws; for example, in deriving the household energy requirement from each of the individuals in the household, it does not comply with the nutritional expert group's recommendation about applying energy requirements to groups rather than single individuals of a given sex and age (WHO, 1985; FAO, 2004). Another flaw is that in deriving the IFPRI-MDER, the value obtained is not a minimum acceptable level of energy requirement, because it takes the median reference body weight, which is the 50th percentile of the distribution of WHO growth standards for a given sex and age group, for light physical activity or a sedentary life style. The estimated MDER using the IFPRI approach is therefore an average of energy requirements for light physical activity or a sedentary life style, and not a minimum. A third flaw, which is also a flaw of the first approach, is the direct comparison of household energy consumption, which refers to a very short household reference period and ignores the effect of seasonal variation and other undesirable sources of variation on implied inequality of energy consumption. This results in overestimation of the prevalence of food deprivation, owing to an overestimated implicit variation in the distribution within the population and to an overestimated MDER, as documented elsewhere (Sibrian, Naiken and Mernies, 2007) and available at www.fao.org/faostat/foodsecurity/papers_en.htm.

FAO methodology has used a third approach. In estimating the prevalence of food deprivation, this approach uses a parametric distribution framework under the assumption that DEC per person per day follows a log-normal distribution. FAO Statistics Division has tested the log-normality assumption against other distributions, using household surveys from countries in different continents. The approach depends on three key parameters for each population group: the average DEC per person per day (total energy consumed by the entire population divided by the population size); the level of inequality in access to that energy consumption within the population; and the MDER for the population group. Two components measure inequality in access to energy consumption: the coefficient of variation (CV) of energy consumption due to income, and the CV of energy consumption due to biological factors (sex, age and physical activity). The former reflects the variation among means of energy consumption by income deciles, grouped on a per person basis. The latter reflects variations in the sex and age composition structure data collected in population censuses, as well as variations in body weight for attained heights collected in anthropometric surveys. The FAO/WHO/UNU Expert Consultation on Energy Requirements (FAO, 2004) derived MDER for given age and sex population groups. The body weight is the minimum acceptable weight for attained height (the fifth percentile of the WHO growth standards) and the minimum acceptable physical activity level is that of a sedentary life style.

Of these three approaches, the parametric approach provides the best statistical framework. It takes into account the amount of dietary energy consumed, the inequality in access to energy consumption within the population due to biological and income factors, and a nutritionally grounded MDER. The estimating procedures of this approach are detailed in FAO, 2003 available at www.fao.org/faostat/foodsecurity/files/undernourishment_methodology.pdf.

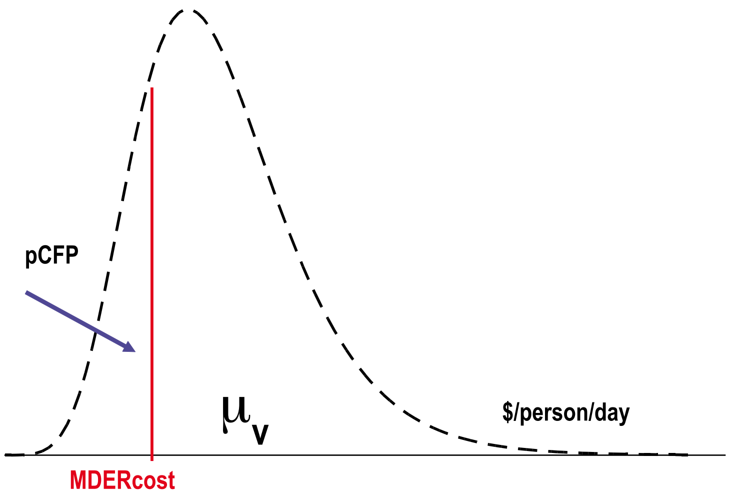
Statistical framework for estimating critical food poverty

The prevalence of critical food poverty is the proportion of the population below the minimum level of income to acquire food to meet MDER, which is the same cut-off value for estimating the prevalence of food deprivation. The definition of the prevalence of critical food poverty using a probability distribution framework is similar to that of the prevalence of food deprivation, as follows:

$$P(CFP) = \int_{v<MDER\cos t} g_v(v)dv = G_v(MDER\cos t)$$

where *P(CFP)* is the proportion of critical food poverty in the total population; *(v)* = income (US$/person/day); *MDERcost* is a cut-off point reflecting the cost of food (US$/person/day) to provide MDER; *g(v)* is the density function of income or proxy total expenditure, shown on the right hand side of Figure 14.2; and *Gv* is the corresponding cumulative distribution function of income.

FIGURE 14.2.
Probability distribution framework for estimating critical food poverty



In Figure 14.2, the curve g(v) depicts the proportion of the population corresponding to different per person per day income levels (v), represented by the horizontal line. The area under the curve up to MDERcost represents the proportion of the population with insufficient income to acquire food to meet MDER, pCFP. The linkage between P(U) and pCFP is MDER. When estimating P(U), MDER is in energy value, while for PCFP it is in monetary value, that is, the cost of MDER (MDERcost).

The proposed pCFP uses the parametric approach with three key parameters for each population group, similar to the P(U): average income per person per day; level of inequality in access to income within the population; and MDERcost.

The average income per person per day is the total income of the whole population divided by the population size. The CV of income measures the inequality of income, which under the log-normality distribution assumption is a one-to-one function of the traditional Gini coefficient. Estimation of the MDERcost uses the prices of food consumed by households in the lowest income quintile, ranked on an income-per-person-per-day basis. The dietary energy unit value for estimating MDERcost is derived from the nutritionally balanced contributions to total energy from proteins (12.5 percent), fats (22.5 percent) and carbohydrates (65 percent), using protein, fat and carbohydrate unit values from the recommendations of the Joint WHO/FAO Expert Consultation of 2002.

DATA REQUIREMENTS

The data needed to estimate both the P(U) and the pCFP indicators are as follows: 1) food consumed, in quantities and monetary value; 2) income, or proxy total expenditure; 3) sampled population, by age and sex; and 4) average height, by age and sex.

It is preferable to record the food items consumed in local monetary values corresponding to standard measurement units (kilograms, grams, litres or millilitres). It is also necessary to describe in as much detail as possible the food items consumed in the sampled households, to help their identification in food composition tables when estimating the level of energy and the main energy-yielding nutrient (proteins, fats and carbohydrates) consumption. The energy, protein, fat and carbohydrate consumption levels and the food monetary value allow estimation of the energy and macronutrient monetary unit values. Estimation of the monetary value of the balanced MDER uses these unit values, that is, the cut-off value MDERcost. Food quantities and monetary values should refer to the food consumption (and not to food acquisition) of the members of the sampled households within the household reference period, regardless of when the food consumed was acquired or produced.

Estimation of the income data uses an aggregated value of all income components for all members of the sampled households based on the concepts and definitions in United Nations manuals. Household income deciles can be defined by ranking households according to income per person per day. Average income estimates by income decile permit estimation of the CV of income. Average energy consumption estimates by income decile permit estimation of the CV of energy consumption due to income. The CV of energy consumption due to biological factors is assumed to be constant at 20 percent, or can be estimated from available anthropometric data based on an induced distribution of energy requirements derived from the observed distribution of body weight for attained height in the population group.

Data on height and population, by age and sex, permit the estimation of MDER using the recommendations of the 2001 Joint FAO/WHO/UNU Expert Consultation on Human Energy Requirements. WHO growth standards, using the average attained height for given age and sex derived from anthropometric surveys, provide the minimum acceptable reference weight for height, for given age and sex. Countries have conducted these surveys as demographic and health surveys (DHS) on children and women of reproductive age, as multiple indicator cluster surveys (MICS) on children, and as other national nutritional surveys. NHS of specific population groups permit derivation of the age and sex population structure.

ESTIMATING PROCEDURES

Estimating the prevalence of food deprivation

The proportion of the population below the MDER is estimated as follows:

Φ [($\log_e$ MDER -μ) / σ)] where Φ is the standard normal cumulative distribution.

It is assumed that the distribution of DEC, f(x), as indicated previously, is log-normal. The parameters μ and σ are estimated by using the mean DEC and CV of DEC, *CV(x),* as follows:

$$\sigma = [\ \log_e (CV^2(x) + 1)\ ]^{0.5} \text{ and } \mu = \log_e \mu(x) - \sigma^2 / 2$$

The average DEC per person per day is:

$$\mu(x) = \sum_{j=1}^{k} f_j\,(x \mid v)_j \Big/ \sum_{j=1}^{k} f_j$$

and the standard deviation of DEC due to income is:

$$\sigma(x \mid v) = \sqrt{\left[\sum_{j=1}^{k} f_j\,(x \mid v)_j^2 - \left(\sum_{j=1}^{k} f_j\,(x \mid v)_j\right)^2 \Big/ \sum_{j=1}^{k} f_j\right] \Big/ \left(\sum_{j=1}^{k} f_j - 1\right)}$$

Where: *k* is the number of income deciles; f_j is the number of sampled households; and $(x|v)_j$ is the average DEC per person per day of the *jth* income or proxy total expenditure decile.

The CV of DEC due to income, CV($x|v$), is formulated as follows:

$$CV(x|v) = \sigma(x|v) / \mu(x)$$

Thus, the data required for estimating CV($x|v$) are the averages of DEC per person per day, the average household size by income group, using deciles of income (or total expenditure) per person per day.

The CV(x) of DEC is formulated as follows:

$$CV(x) = \sqrt{CV^2(x \mid v) + CV^2(x \mid r)}$$

CV($x|r$) is the CV of DEC due to biological factors, which on average has been estimated as 20 percent; however, if data on height for given age and sex are available for the entire population, CV($x|r$) can be estimated based on the induced distributions of weight for attained height and physical activity levels for the population groups.

The right-hand column of Table 14.1 presents the average DEC and in the middle column the average of household members both by decile of household total expenditure from a recent self-weighted sampling NHS (on a sample of 10000 households). It shows the prevalence of food deprivation for aggregated data from a hypothetical example. The estimates of parameters μ and σ are 7.495 and 0.244, respectively, derived from estimates of the CV of DEC due to income, CV($x|v$), and the average DEC, μ(x), as indicated above. This paper treats the estimate of MDER as exogenous. The estimated prevalence of food deprivation is 45.5 percent.

MDER is estimated using the attained height data collected from a representative sample of individuals in the given age and sex population groups.

TABLE 14.1
Estimating P(U) from 10000 sampled households

income decile ($/person/day)	average persons	average dietary energy consumption (Kcal/person/day)
1	6.5	1500
2	6.0	1600
3	5.5	1700
4	5.0	1800
5	4.5	1900
6	4.0	2000
7	3.5	2100
8	3.0	2200
9	2.5	2300
10	2.0	2400
all	**4.3**	**1853**
CV(due to income)	0.146	
CV(x)	0.248	
sigma	0.244	
mu	7.495	
mder	1750	exogenous
P(U)	45.5	percent

The procedure involves using the minimum reference weight for height (the fifth percentile in the WHO growth standards) derived from the data collected on attained height and the energy requirement per kilogram, which differs by age and sex in children, adolescents and adults. The procedure for deriving MDER for the total population is weighted by the age and sex structure of the population under study.

Estimating the prevalence of critical food poverty

The procedure for estimating the prevalence of critical food poverty (pCFP) is similar to that for estimating the prevalence of food deprivation, except that it is based on income distribution and the minimum cost of macronutrient-balanced MDER. The process for evaluating pCFP is as follows:

Φ [($\log_e$ MDERcost -μ) / σ)] where Φ is the standard normal cumulative distribution.

It is assumed that the distribution of income or proxy total expenditure, g(v), as indicated previously, is log-normal, with parameters μ and σ estimated on the basis of the mean income (or proxy total expenditure) and CV of income CV*(v)*, as follows:

$$\sigma = [\ \log_e (CV^2 (v) + 1)\ ]^{0.5} \text{ and } \mu = \log_e \mu(v) - \sigma^2 / 2$$

The average income per person per day is:

$$\mu(v) = \sum_{j=1}^{k} g_j (v)_j / \sum_{j=1}^{k} g_j$$

and the standard deviation of income is:

$$\sigma(v) = \sqrt{\left[\sum_{j=1}^{k} g_j (v)_j^2 - (\sum_{j=1}^{k} g_j (v)_j)^2 / \sum_{j=1}^{k} g_j\right] / (\sum_{j=1}^{k} g_j - 1)}$$

Where *k* is the number of income decile; g_j is the number of sampled households; and $(v)_j$ is the average income (or proxy total expenditure) per person per day of the *jth* income (or proxy total expenditure) decile.

Formulation of the CV of income, CV(*v*), is as follows:

$$CV(v) = \sigma(v) / \mu(v).$$

Thus, the data required for estimating CV(*v*) are average income (or proxy total expenditure) per person per day, and average household size, by household per person per day income or expenditure decile.

The right hand column of Table 14.2 presents the average income (or proxy total expenditure) per person per day and in the middle column the average of members by decile of household income (or proxy total expenditure) per person per day from the self-weighted NHS used for estimating critical food poverty.

TABLE 14.2
Estimating pCFP from 10000 sampled households

income decile ($/person/day)	average persons	average income ($/person/day)
1	6.5	0.45
2	6.0	0.55
3	5.5	0.65
4	5.0	0.90
5	4.5	1.20
6	4.0	1.80
7	3.5	2.50
8	3.0	4.00
9	2.5	7.00
10	2.0	10.00
all	**4.3**	**2.00**
cv	**1.21**	
sigma	0.951	
mu	0.243	
mdercost	0.61	exogenous
pCFP	21.7	percent

It shows the prevalence of critical food poverty for aggregated data from a hypothetical example. The estimates of parameters μ and σ are 0.243 and 0.951, respectively, derived from estimates of the CV of income, CV(*v*), and the average total expenditure, μ(v), as indicated above. Estimate of MDERcost is 0.61 for balanced-MDER. The estimated prevalence of critical food poverty is 21.7 percent.

Estimation of MDERcost takes place by using MDER and the costs of proteins, fats and carbohydrates from households in the lowest income (total expenditure) quintile.

EXAMPLES

Many countries have estimated both indicators when assessing food insecurity derived from NHS data. Figures 14.3 and 14.4 illustrate results of both indicators for Georgia (Georgia, 2007) and Lao People's Democratic Republic (Lao PDR, 2007).

FIGURE 14.3.
Georgia 2004: households with young children

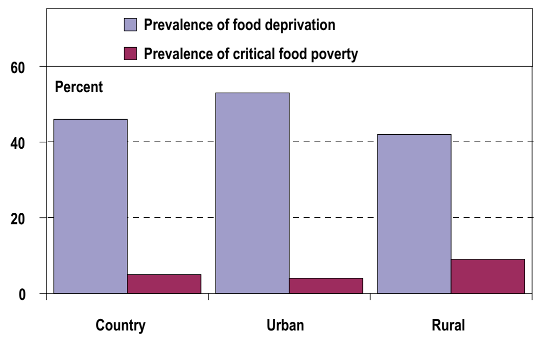
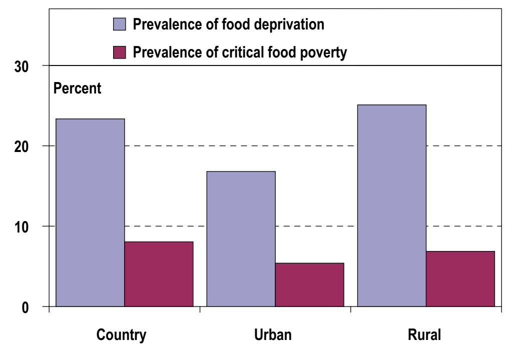


FIGURE 14.4.
Lao PDR 2002/2003: all households



CONCLUSION and REMARKS

Countries can monitor MDG targets on poverty and hunger reduction, based on NHS data on food consumption and income, at national and sub-national levels.

The indicators of food deprivation and critical food poverty discussed in this paper can be used to assess magnitude and trends obtained by using standard estimating procedures from NHS for the identification of food-insecure population groups and for evaluation of the social and economic impact of policies and interventions that aim to improve food security.

REFERENCES

FAO. 2003a. *Measurement and assessment of food deprivation and undernutrition: Proceedings of the International Scientific Symposium.* Rome, 26-28 June 2002. Rome, FIVIMS, FAO. Available at www.fivims.net/static.jspx?lang=en&page=iss.

FAO. 2003b. *Methodology for the measurement of food deprivation.* Rome, Statistics Division, Food Security Statistics. Available as metadata at www.fao.org/faostat/foodsecurity/index_en.htm.

FAO. 2004. *Human Energy Requirements - Report of a Joint FAO/WHO/UNU Expert Consultation.* Rome, 17-24 Oct. 2001. FAO Food and Nutrition Technical Report Series No. 1. Rome. Available at www.fao.org/docrep/007/y5686e/y5686e00.htm.

Georgia. 2007. *Food insecurity assessment based on food consumption statistics derived from Georgian 2005 Integrated Household Survey: preliminary draft report.* Tbilisi, Ministry of Economic Development/Department of Statistics.

Lao PDR. 2007. *Food insecurity assessment based on food consumption statistics derived from the 2002/03 Lao PDR Expenditure and Consumption Survey.* Vientiane, NSC.

Sibrián, R. 2006. Indicators for monitoring hunger at global and sub-national levels. In *First World Congress of Public Health Nutrition Congress Proceedings.* Barcelona, Spain.

Sibrián, R., Naiken, L. & Mernies, J. 2007. *The FAO parametric versus the IFPRI nonparametric approach to estimating the prevalence of undernourishment: Issues relating to the use of household level data from national household surveys.* FAO Statistics Division Working Paper Series No. ESS/ESSG/012e. Available at www.fao.org/es/ess/faostat/foodsecurity/papers_en.htm.

Sibrián, R., Ramasawmy, S. & Mernies, J. 2007. *Measuring hunger at sub-national levels from household surveys using the FAO approach: Manual.* FAO Statistics Division Working Paper Series No. ESS/ESSA/005e. Available at www.fao.org/es/ess/faostat/foodsecurity/papers_en.htm.

Smith, L.C., Alderman, H. & Aduayom, D. 2006. *Food insecurity in sub-Saharan Africa, new estimates from household expenditure surveys.* IFPRI Research Report No. 146. Washington DC, International Food Policy Research Institute (IFPRI).

WHO. 2003. *Report of a Joint WHO/FAO Expert Consultation on Diet, Nutrition and the Prevention of Chronic Diseases.* WHO Technical Report Series No. 916. Geneva. Available at http://www.fao.org/wairdocs/who/ac911e/ac911e00.htm.

WHO. 2007. *World Health Organization Global Database on Child Growth and Malnutrition.* Geneva, WHO Department of Nutrition for Health and Development.

Part 7.

Glossary

ANTHROPOMETRY
Use of human body measurements to obtain information about nutritional status.

AVERAGE ENERGY REQUIREMENT
It refers to the amount of energy considered adequate to meet the energy needs for normative ***average*** acceptable weight for attained height while performing ***moderate*** physical activity in good health.

BALANCED DIET
The diet is balanced when it is judged to be consistent with the maintenance of health in a population. The balance can be examined in terms of the contribution of the various energy-yielding macronutrients and other nutrients. A macronutrient-based balance food consumption pattern should contribute to total energy from proteins, fats and carbohydrates within recommended ranges as follows: proteins from ten to 15 percent, fats from 15 to 30 percent and carbohydrates from 55 to 75 percent, as from a technical report of a 2002 Joint WHO/FAO Expert Consultation (WHO 2003).

CRITICAL FOOD POVERTY
The prevalence of critical food poverty (pCFP) refers to the proportion of persons living on less than the cost of the macro-nutrient balanced MDER (for Minimum Dietary Energy Requirement see below and for balanced diet see above) with food prices from households in the lowest income quintile. It can be estimated at national and sub-national levels.

DEGREE OF FOOD DEPRIVATION
A measure of the overall food insecurity situation in a country, based on a classification system that combines prevalence of undernourishment, i.e. the proportion of the total population suffering from a dietary energy deficit, and depth of undernourishment, i.e. the magnitude of the undernourished population's dietary energy deficit.

DEPTH OF FOOD DEPRIVATION
It refers to the difference between the average dietary energy intake of an undernourished population and its average minimum energy requirement (MDER).

DIETARY ENERGY UNIT COST
The dietary energy unit cost is the monetary value in local currency of 1000 kilo-calories of food consumed.

DIETARY ENERGY CONSUMPTION
Food consumption expressed in energy terms. At national level, it can be calculated from the FBS (see below); the FBS estimate refers to both private (households) and public (hospitals, prisons, military compounds, hotels, residences, etc) food consumption. At sub-national levels it is estimated using food consumption data, with quantities collected in national household surveys (NHS); these estimates refer to private food consumption.

DIETARY ENERGY DEFICIT
Same as Depth of Food deprivation.

DIETARY ENERGY INTAKE
The energy content of food consumed.

DIETARY ENERGY REQUIREMENT

It refers to the amount of energy required by individuals to maintain body functions, health and normal physical activity.

DIETARY ENERGY SUPPLY

Food available for human consumption, expressed in kilocalories per person per day (kcal/person/day). At country level, it is calculated as the food remaining for human use after deduction of all non-food consumption (exports, animal feed, industrial use, seed and wastage)

FOOD BALANCE SHEETS

Food Balance Sheets (FBS) are compiled every year by FAO, mainly with country-level data on the production and trade of food commodities. Using these data and the available information on seed rates, waste coefficients, stock changes and types of utilization (feed, food, processing and other utilization), a supply/utilization account is prepared for each commodity in weight terms. The food component of the commodity account, which is usually derived as a balancing item, refers to the total amount of the commodity available for human consumption during the year.

FOOD CONSUMPTION DISTRIBUTION

Food consumption distribution refers to the variation of consumption within a population. It reflects both the disparities due to socio-economic factors and differences due to biological factors, such as sex, age, body-weight and physical-activity levels.

FOOD DEPRIVATION

Food deprivation refers to the condition of people whose food consumption is continuously below its requirements. FAO's measure of food deprivation refers to the proportion of the population whose dietary energy consumption is below the minimum energy requirement (see below).

FOOD INSECURITY

A situation that exists when people lack secure access to sufficient amounts of safe and nutritious food for normal growth and development and an active and healthy life. It may be caused by the unavailability of food, insufficient purchasing power, inappropriate distribution, or inadequate use of food at the household level. Food insecurity, poor conditions of health and sanitation, and inappropriate care and feeding practices are the major causes of poor nutritional status. Food insecurity may be chronic, seasonal or transitory.

FOOD SECURITY

A situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life.

GINI COEFFICIENT

The Gini coefficient measures the extent to which the distribution of income (or, in some cases, consumption expenditure, food dietary energy consumption) among individuals or households within an economy deviates from a perfectly equal distribution. A Lorenz curve plots the cumulative percentages of total income received against the cumulative number of recipients, starting with the poorest individual or household. The Gini coefficient measures the area between the Lorenz curve and a hypothetical line of absolute equality, expressed as a percentage of the maximum area under the line. Thus a Gini coefficient index of 0 represents perfect equality, while an index of 100 implies perfect inequality.

GINI COEFFICIENT DUE TO INCOME

The Gini coefficient is a measure of inequality in food consumption when income is used as the grouping variable and ranges from 0 (when income has no effect on food consumption) to one (when food consumption depends only on income). It can refer to inequality in food consumption due to income in monetary or in energy terms.

HOUSEHOLD CONSUMPTION EXPENDITURE

Household consumption expenditure refers to all monetary expenditure by the household and individual members on goods intended for consumption and expenditure on services, plus the value of goods and services received as income in kind and consumed by the household or individual members of the household. Thus the value of items produced by the household and utilised for own consumption, as well as the net rental value of owner-occupied housing and the gross rental value of free housing occupied by the household, each represent part of household consumption expenditure.

HOUSEHOLD FOOD CONSUMPTION EXPENDITURE

This refers to food consumed by household members during a specified period, at home and away from home, for example, at restaurants, bars, the work place, school, and so on. It includes food from all sources, purchased or from garden or farm. Further deductions should be made to allow for food given away to other households or non-household members and visitors as well as for wastage and losses occurring after acquisition.

HOUSEHOLD EXPENDITURE

Consumption plus non-consumption expenditure made by the household, both including food.

HOUSEHOLD NON CONSUMPTION EXPENDITURE

It refers to income taxes, other direct taxes, pension and social security contributions, remittances, gifts and similar transfers made by the household in monetary terms or in kind, including food such as given away, raw or ready to eat.

HOUSEHOLD INCOME

Income is the sum of all receipts, in money or in kind, which as a rule are received regularly and are of recurring nature, including food.

INCOME ELASTICITY OF FOOD DEMAND

The income elasticity of food demand measures the responsiveness of the quantity, monetary or nutrient value demanded of a good, to the change in the income of the people demanding the good. It is calculated as the ratio of the percent change in quantity demanded to the percent change in income.

INCOME INEQUALITY

Income inequality refers to disparities in the distribution of income.

INEQUALITY IN FOOD CONSUMPTION DUE TO INCOME

The inequality refers to the variation of the food consumption level within a population due to disparities in income distribution.

KILOCALORIE (KCAL)

The kilocalorie is a unit of measurement of dietary energy. In the International System of Units (ISU), the universal unit of dietary energy is the joule (J) but Kcal is still commonly used. One kilocalorie = 4.184 kilo-joules (KJ).

MACRONUTRIENTS

Used in this document to refer to the proteins, carbohydrates and fats that are required by the body in large amounts and that are available to be used for energy. They are measured in grams.

MICRONUTRIENTS

Refer to the vitamins, minerals and certain other substances that are required by the body in small amounts. They are measured in milligrams or micrograms.

MINIMUM DIETARY ENERGY REQUIREMENT

In a specified age/sex category, this refers to the amount of dietary energy per person required for a minimum acceptable body-weight for attained-height and carry out a ***light*** physical activity. For an entire population, the minimum energy requirement is the weighted average of the minimum energy requirements of the different age/sex groups in the population. This is expressed as kilocalories per person per day.

NUTRITIONAL STATUS

The physiological status of an individual that results from the relationship between nutrient intake and requirement and from the body's ability to digest, absorb and use these nutrients. Lack of food as well as poor health and sanitation and inappropriate care and feeding practices are the major causes of poor nutritional status.

SHARE OF FOOD EXPENDITURE

The proportion of household consumption expenditure allocated to food; it is also known as the Engel ratio.

UNDERNOURISHMENT

Undernourishment refers to the condition of people whose dietary energy consumption is continuously below a minimum dietary energy requirement for maintaining a healthy life and carrying out a light physical activity. The number of undernourished people refers to those in this condition.

UNDERNUTRITION

The result of undernourishment, poor absorption and/or poor biological use of nutrients consumed.

ISBN 978-92-5-106110-7

9 789251 061107

TC/M/I0430E/1/10.08/500