# Towards the Measurement of Household Resilience to Food Insecurity: An Application to Palestinian Households

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**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 – e.g. the complexity (multidimensionality) of the concept of food security and the unpredictability of the many shocks that cause food insecurity – and empirical – e.g. the absence of longitudinal data over a period of time long enough to enable the various sources of risk to express themselves, thereby allowing the analysis of trends and risks.

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

We have developed an index of household resilience to food insecurity according to four building blocks: income and food access; assets; access to services; and social safety nets. Furthermore, stability and adaptive strategies are two other dimensions that cut across these building blocks and for households' capacity to respond and adapt to shocks. The empirical strategy has been implemented using the Palestinian Public Perception survey data set. The process of building the indexes involved the use of decision matrices and multivariate methods (factor analysis, cluster analysis, principal component analysis, etc.). The validation of the decision rules for building the indexes has been done through CART (Classification and Regression Tree) 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.

## 1. Introduction

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

"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, what strategies to implement ex-ante and ex-post to manage and cope with risks, etc.).

The consequence of acknowledging this is important both in terms of analytical content (what is the subject of the analysis?) and methodology (how should we analyze it?). This also 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*.

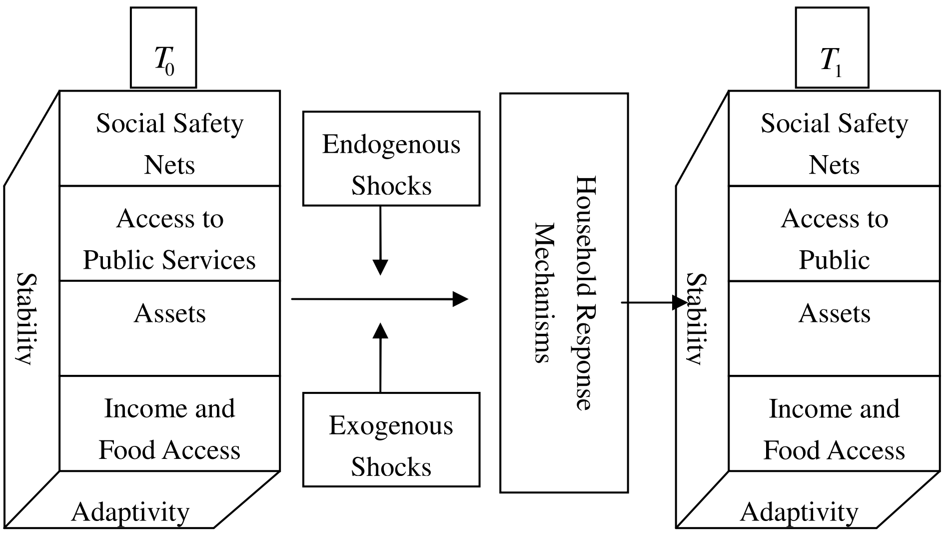
Levin *et al*. (1998) argue that resilience offers a helpful way of thinking about the evolution of social systems, partly because it provides a means of analyzing, measuring and implementing the sustainability of such systems. This is largely because resilience shifts attention away from long-run equilibria, and towards the system's capacity to respond to short-run shocks and stresses in a constructive and creative way. Diversity does not support stability yet it does support resilience and system functioning (Holling, 1973 and 1986), while rigid control mechanisms that seek stability usually 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 at measuring 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).

## 2. The Conceptual Model and Methodology

### 2.1. The model

The conceptual framework in figure 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.

**Figure 1. Resilience conceptual framework.**



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. government, international institutions, etc.), which might themselves be causes of the 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 1. In algebraic terms, the following equation estimates the resilience indicator for household $i$:

$$R_i = w_{IFA} IFA_i + w_{APS} APS_i + w_{SSN} SSN_i + w_S S_i + w_{AC} AC_i + \varepsilon_i \tag{1}$$

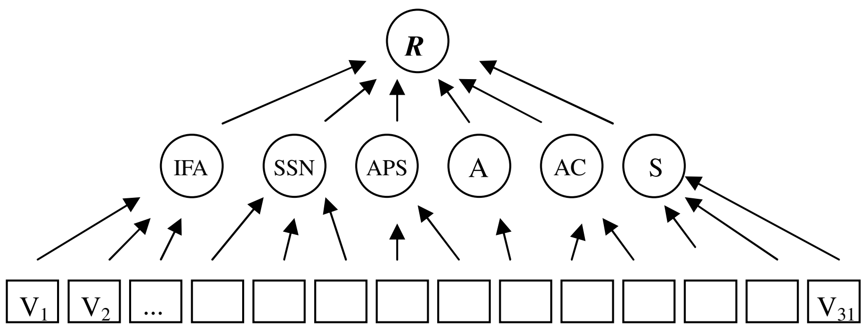
where, $R$ = Resilience, $S$ = Stability, $SSN$ = Social Safety Nets, $APS$ = Access to Public Services, $A$ = Assets, $IFA$ = Income and Food Access, $AC$ = Adaptive Capacity and $w_k$ = the weight for the $k$-th block in defining resilience.

Resilience is a latent variable depending on the terms on the right hand side. Therefore, in order to estimate $R$ we have to estimate separately *IFA, S, SSN, APS, A, AC*, which are themselves latent variables. They are variables not directly observed in the survey, but it is possible to estimate them through some 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.

### 2.2. Methodological Approaches

The model described in the previous section is an extension of multivariate regression models. In our case, we have a hierarchical model where some of the variables are dependent from one side and independent from the other. Moreover, we have also to deal with unmeasured variables (latent). Figure 2 shows the path diagram of the model we are dealing with.

**Figure 2. Path Diagram of the household's Resilience Model**




In the causal models literature (Spirtes *et al.*, 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 that case, the regression properties are extended to the multi-level models. One of the innovative parts of this paper is the adoption of models for latent variables in complex survey data.
Considering the complexity of the model that we are dealing with, the following approaches can estimate household resilience:

1. Structural equation models (SEM) are the most appropriate tool to deal with the kind of model described above. Structural equation modeling combines the ideas of factor analysis with regression. One assumes the set of measured variables to be an imperfect measure of the underlying latent variable of interest. Structural equation modeling uses a factor analysis type model to measure the latent variables via observed variables and simultaneously it uses a regression type model for the relationship among the latent variables (Bollen, 1989). Generally, the estimation methods developed for structural equation models have been limited to the normally distributed observed variables but, in most cases (included ours), many variables are categorical or ordinal..

*2.* The other approach explored is a multi-stage approach separately measuring the latent variables through the observed variables. This involve the use of various sets of observed variables (represented as squares in Figure 2) to estimate the specific latent variables (circles in Figure 2). In other words, the circles 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, thus it is necessary to use different methods for different types of variables. The methods commonly used for this kind of analysis: *i) Structural Equation Models (SEMs) ii) Factorial Analysis (FA) iii) Principal Components Analysis (PCA) iv) Cluster Analysis (CA), v) Lisrel Methods.*

These methods are usually combined with deterministic decision matrixes which are based on prior knowledge of the variables. An auxiliary tool for data mining purposes is the Classification and Regression Trees (CART) methodology, which it is possible to use also for testing the validity of the adopted model.
We decided to adopt the second strategy for measuring resilience, for the following reasons: i), the variables available are not all normally distributed and this may require the use of different multivariate techniques; and ii), measuring the different components separately makes the model more flexible, permitting the inclusion of prior information and solving the parameter identification problem.

### 2.3. The data set

The Palestinian Public Perception Survey (PPPS) data is an interagency effort aiming 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; The responsibility for the data collection lied with the Palestinian Central Bureau of Statistics. The PPPS provides a very rich data set, including key indicators relevant for defining and analyzing 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 due to some changes made in the food security section of the questionnaire, which make the last survey incompatible with previous ones. The sample size was 2,184 households and the sampling design was a two-stage stratified cluster.
The presentation of the process of variable selection and elaborating them to obtain unique indicators is in the next section.

## 3. The Application of the resilience model to the Palestinian Data

The analytical framework will follow a three step procedure: i) identification and processing of selected variables for each resilience block; ii) development of decision matrixes and multivariate methods (factor analysis, cluster analysis, principal components analysis, etc.) to build the indicator for each block; and iii) application of the Classification and Regression Trees (CART) methodology to build precise splitting rules based on the regression tree for a better understanding of the whole process. The use of CART will also allow the validation of the decision process and the identification of those factors (indicators) that play a major role within the different blocks.

The variable selection procedures for the generation of the indicators for each building block are particularly complex in the resilience framework where the multidimensional correlations often make individual variables relevant to several blocks. The conceptual model described in section 3.1 simplified this issue a lot.

- Income and Food Access (*IFA*)

The generation of the *IFA* indicator has involved the use of the following five indicators: *i) average per person daily income (NIS/person/day), ii) average per person daily consumption expenditure (food and non-food), iii) average dietary energy consumption (DEC - kcal/person/day[1]), iv) household food insecurity access score (HFIAS)[2], v) dietary diversity and food frequency score[3] (DD).*

To generate the income and food access (IFA) indicator we have run a factor analysis using the principal factor method and the scoring method suggested by Bartlett (1937). Table 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 since the score increases when food security decreases.

**Table 1. Eigenvalues**

| Factor | Eigenvalue |
|---|---|
| Factor1 | 1.82865 |
| Factor2 | 0.18174 |
| Factor3 | -0.10394 |
| Factor4 | -0.11670 |
| Factor5 | -0.21905 |

**Table 2. Factor loadings and correlations**

| Variable | Factor1 | 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*)

The public services considered in the analysis are the following: *i) physical access to health (ordinal); ii), Health care quality score (continuous); iii) Quality of Educational System (ordinal); ii) Perception of Security, (ordinal); iii) Mobility and Transport Limitations (ordinal);, iv) Water, Electricity and Phone networks (ordinal);*

Spatial distribution is a key factor for access to public services. We cannot assume that the relevance of the different services is constant among the different regions. For this reason, we decided to run different factor analysis for the five sub-regions: North West Bank, Middle West Bank, East Jerusalem (considered separately for the different socio-economic characteristics with Middle WB), South West Bank and Gaza Strip. Table 3 shows the scoring coefficients of the Bartlett method for each sub-regional area. The missing values for this block have been imputed using the mean at governorate level.

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[1]Sibrian *et al.* 2006

[2]Coates *et al.*, 2006

[3]*Hoddinott, J. and Yohannes, Y., 2002.*

**Table 3. Bartlett's Scoring Coefficients**

| | North WB | Middle WB | Jerusalem | South WB | Gaza Strip |
|---|---|---|---|---|---|
| Health physic. 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... | 0.09623 | 0.15815 | -0.07116 | 0.35888 | -0.45009 |

- Social Safety Nets (*SSN*)

The variables used for the generation of the SSN indicator are the following:

*i) Amount of Cash and In-kind Assistance (continuous variable in NIS/person/day), ii) Goodness of Assistance (ordinal scale, 4 classes), iii) Job Assistance (binary response, yes/no), iv) Monetary value of 1st and 2nd type of assistance (continuous variable in NIS/person/day), v) Evaluation of the main type of assistance (ordinal scale, 4 classes), vi) Frequency of assistance (count, # of received assistance in the last 6 months), vii) Overall opinion on targeting (categorical; assistance targeted to the needy, even to some not needy; and targeted without distinction)*

Even in this case, missing values have been treated using the mean at governorate level. Different multivariate exploratory techniques (PCA, FA and CA) have been used to find the common pattern in the data but there was not a good performance of the different tools due 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 the following[4]:

```
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*)

Information on assets was not available in the PPPS data set and therefore we decided not to use proxies for it so as not to contaminate the estimates.

- Adaptive Capacity (*AC*)

The adaptive capacity is measured by the following indicators: *i) Diversity of income sources (count 1 to 5), ii) Coping Strategy index (quantitative 1 to 16), iii) Capacity to keep up in the future (ordinal 1 to 5), iv) Number of Assistance Sources (count 1 to 6)*

The first variable indicates the number of *income sources from different sectors* (public, private etc...), e.g. during a crisis, the more sources of income the family 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 HHs. The weight for AC_4 has been used maintaining invariant 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
```

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

- Stability ($S$)

The variables used for the measurement of stability are the following: *i) Professional Skills (continuous), ii) Educational Level (continuous), iii) Employment Ratio (ratio, from 0 to 1) , iv) Number of HH members that have lost their job (continuous), v) Income Stability (ordinal; increased, the same, decreased), vi) Assistance Dependency (ratio, from 0 to 1), vii) Assistance Stability (ordinal; increased, the same, decreased), viii) Health Stability (count, 0 to 8) and ix) Educational System Stability (ordinal; increased, the same, decreased)*

In this case, given the multidimensionality of the feature, no prior decisions were taken. We ran a factor analysis to analyze the correlation matrix using the iterated principal-factor (ipf) method. This method re-estimates the communalities iteratively. Then, the Bartlett method was used to generate the $S$ indicator. Table 4 shows the correlation coefficients of the $S$ indicator with the original variables.

**Table 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 ($R$)

The indicators estimated in the previous paragraphs become covariates in the estimation of resilience. Recalling equation (1) we have:

$$R_i = w_{IFA}\hat{IFA} + w_{APS}\hat{APS}_i + w_{SSN}\hat{SSN}_i + w_S\hat{S}_i + w_{AC}\hat{AC}_i + \varepsilon_i \qquad (2)$$

For exploratory purposes we have run a factor analysis using the iterated principal factor method. Table 5 shows the eigenvalues which indicate that the first two factors are relevant and Table 6 shows the factor loadings for the first two factors.

**Table 5. Eigenvalues**

| | Eigenvalue |
|---|---|
| Factor 1 | 1.19054 |
| Factor 2 | 0.334 |
| Factor 3 | 0.1423 |
| Factor 4 | 0.04417 |
| Factor 5 | -0.00019 |

**Table 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 6 shows that factor 1 does not capture the information regarding social safety nets but that factor 2 does. For this reason, we decided to use approximated weights, which account for both factors. Finally, the following equation measured the resilience indicator:

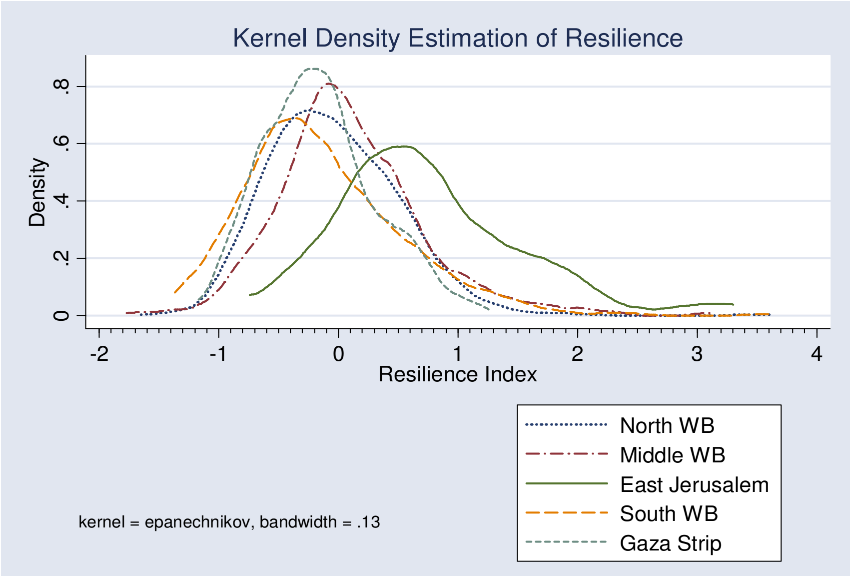
```
R = (2*stdIFA + stdAPS + stdAC + stdS + 0.5*stdSSN)/5.5
```

The coefficients used in the measurement of resilience are approximately proportional to the sum of the factor loadings in table 6. The coefficient 2 for the standardized *IFA* represented the only difference. We did this to place greater emphasis on household capital considering the lack of information on assets. The next section represents and discusses the results of these estimates.

## 4. Discussion of Results

This section presents some of the estimates of the resilience index and its components in the 5 sub-regions of Palestine. The following figure shows the Epanechnikov's kernel density estimates of the resilience distribution. The presentation of the results involved the use of the nonparametric method due to its major informative capacity.

**Figure 3. Resilience in the 5 Palestinian sub-regions.**




The figure shows the gap between East Jerusalem and the other 4 regions. At first glance, it looks like the other regions have more or less the same resilience level, so in this case the nonparametric approach is not very helpful. In order to obtain the significance level of the difference we have to go back to the parametric approach. The following table shows the mean and standard deviation for resilience and its standardized components. The matrix in table 8 shows the t-statistics for the pair-comparison between the means of the different regions.

**Table 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 | 2087 | 0 | 0.624 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |

**Table 8. The Matrix of t-statistics for the Comparison between 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: Significant at 95% | | | ** Pr(T < t) = 0.7890: Not Significant | | |

The differences between regional resilience levels are all significant except for between the Gaza Strip and the South West Bank. This is due to the high level of social safety nets in the Gaza Strip. Obviously, 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 value for *R, IFA, AC, S,* but it also has the highest level of inequality since it has the highest standard deviation.

### 5. Model Validation with CART

We are using CART 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, social sector and public services are strictly correlated to the overall resilience indicator. For this reason, some validation procedures are necessary to understand better the relation between resilience and original variables, using the classification and regression tree (CART) methodology (see Steinberg and Colla, 1995; and, Breiman *et al.*, 1984). Such tools also allow us to build the resilience decision tree and the related splitting rules which are very important for gaining an understanding of the key determinants of resilience. Furthermore, the biggest advantage of CART is its cross-validation procedures which allow us to measure the errors in the model. Other advantages of using CART are: *i) Robust nonparametric tool, ii) Capacity to handle complex data structures, iii) Don't require PDF assumptions, iv) Overtake heteroskedasticity and multicollinearity, v) Capacity to deal with missing values, and vi) Transferability of decision rules to new observations*

The target variable for the model implemented with CART was the resilience indicator. Since it is a continuous variable, CART performed a *regression tree* (if the target variable is categorical, CART performs a *classification tree*). The model has included, as predictors, all the original variables used in the empirical approach. The weights deriving from the sample design have been considered too. 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), i.e. 1-0.067 = 0.933. In fact, if you run an OLS regression of the resilience index on the 31 original variables, the R-squared is 0.9825. The CART procedure has included the use of the GINI splitting criterion and the 10-fold cross validation for testing.

The ranking of variable's importance shown in Table 9 explains the role of each variable in defining resilience. This ranking is measured considering main splitters, competitors and surrogates.

**Table 9. Variable Importance**

| Code | Description | Import. | Code | Description | Import. |
|---|---|---|---|---|---|
| I_IFA1 | Income | 100 | APS_4 | Perception of Security | 2,57 |
| IFA_2 | Consumption | 76,65 | APS_5 | Mobility Constraints | 2,13 |
| I_IFA7 | Dietary Energy Consumption | 66,99 | S6 | Assistance Dependency | 1,75 |
| I_AC_2 | Coping Strategies | 50,37 | SSN_4 | Monet. 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 | Educational level | 7,46 | S5 | Income Stability | 1,24 |
| APS_2 | Health Service quality | 6,82 | AC_4 | # of assistance sources | 1,21 |
| I_IFA5 | Dietary Diversity | 6,44 | SSN_6 | Frequency of assistance | 0,83 |
| SSN_2 | Goodness of assistance | 4,95 | SSN_7 | Opinion on targeting | 0,61 |
| SSN_5 | Evaluation Main Assistance | 4,23 | APS_7 | Water, electricity & phone | 0,61 |
| SSN_1 | Cash and In kind assistance | 3,74 | S4 | # HH members have 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 | Educational System | 2,83 | | | |

Another 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.

## 6. Conclusion

The analysis conducted on the 11 PPPS seems to confirm the validity of the conceptual framework adopted. The results are meaningful and the resilience index in the 5 sub-regions has significant differences. The same applies for the 5 components of the resilience model.

However, we acknowledge the constraints on the analysis due to the static nature of the available database. It is necessary to carry out this analysis with panel data as soon as a similar database becomes available. It will be also interesting to extend the analysis to other key studies to assess the robustness of the proposed analytical frame as well as any emerging patterns of resilience.

It will be necessary to test the other methodology proposed in this paper, i.e. the structural equation modelling with Bayesian networks, to see which the most appropriate methodology is.

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

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.

Coates, J., Swindale, A. and Bilinsky, P., 2006. *Household Food Insecurity Access Scale (HFIAS) for Measurement of Food Access: Indicator Guide*. USAID - FANTA, Washington DC.

Breiman,L., Friedman,J., Olshen,R. and Stone,C.,1984. *Classification and Regression Trees*. Pacific Grove: Wadsworth.

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

Folke, C., Berkes, F., and Colding, J., 1998. "Ecological Practices and Social Mechanism for Building Resilience and Sustainability". In Berkes, F., and Folke, C., 1998. *Linking Social and Ecological Systems*. Cambridge: Cambridge University Press: 414-36.

Hemrich, G., and Alinovi, L., 2004. "Factoring Food Systems' Resilience in the Response to Protracted Crisis". In FAO, 2004. *The State of Food Insecurity in the World 2004*. Roma: FAO.

Hoddinott, J. and Yohannes, Y., 2002. *Dietary Diversity as a Household Food Security Indicator*. Washington, D.C.: 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 Clark, W.C., and Munn, R.E., (eds.). *Sustainable Development of the Biosphere*. Cambridge: Cambridge University Press. Pp. 292-317.

Kasperson, J.X., and 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): 222-35.

Mane, E., Alinovi, L., and Sacco, E., 2007. Profiling Food Security in Palestinian Governorates: Some Classification Techniques Based on Household-Level Data. Paper presented to the International Conference on "Statistics and Development", held in Ramallah, on 27-28 March 2007.

Sibrián, R., Ramasawmy, S., and Mernies, J., 2006. Measuring Hunger at Subnational Level: The FAO Approach Applied to Household Survey Data. ESS/ESSA/005 FAO Working Papers. Rome: FAO.

Spedding, C.R.W., 1988. *An Introduction to Agricultural Systems*, 2$^{nd}$ Ed. Barking: Elsevier.

Spirtes, P., Glymour,C., and Scheines, R., 2000. *Causation, Prediction and Search.* Cambridge: MIT Press.

Steinberg, D. and Colla, P., 1995. *CART: Tree-Structured Non-Parametric Data Analysis*. San Diego: Salford Systems.