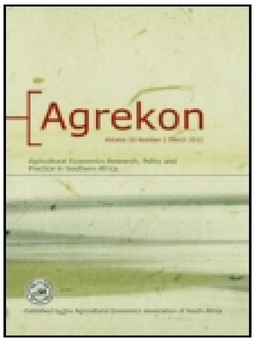

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INDEXING HOUSEHOLD RESILIENCE TO FOOD INSECURITY SHOCKS: THE CASE OF SOUTH SUDAN

L.B. Lokosang[1], S. Ramroop[2] and T. Zewotir

ABSTRACT

Based on a number of household characteristics, livelihood capitals and endowments, we generate a household food security resilience index. The rationale of the paper is premised on the notion that resilience to food insecurity is a property of wealth and thus its proxy. The study explored the statistical robustness and efficiency of the technique in providing evidence for triggering alerts and action for curbing risk of food insecurity uncertainties. It is established that Principal Component Analysis (PCA) is helpful in constructing a summary measure (referred to here as Household Resilience Index or HRI in short) that is an efficient proxy for wealth index, which is based on consumption data, and that predicts per capita consumption very well. The paper elaborates six distinctive characteristics of the HRI that support its adoption and use. The dataset used in the study is from the 2009 South Sudan National Household Baseline Survey.

Keywords: Livelihood capitals, food insecurity, household resilience, asset index, principal components

JEL Classification Codes: C430; C650; O150

1 INTRODUCTION

Compounded by general, macroeconomic poverty, food insecurity has been persistent in Africa, especially in the sub-Saharan region (Devereux and Maxwell, 2011; Smith *et al*., 2006). Based on International Food Policy Research Institute's (IFPRI's) Global Hunger Index (2012), Africa is depicted to have extreme hunger levels in 10 out of 12 countries of the world. The United Nations Development Programme (UNDP) and the World Bank consistently report high poverty levels measured in terms of Purchasing Power Parity (PPP), household daily earnings of 1.25 United States Dollars and per capita food supply of less than 2 200 calories (9 200 kilojoules) per day (The World Bank, 2004; Ahmed *et al*., 2007).

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In the last decade, poverty and development analysts have directed attention to measuring poverty and socio-economic status (SES) based on households' asset-index. Much cited work is that of Filmer and Pritchett (2001) and Palmer *et al*. (2004). Using data from a number of livelihood assessment surveys such as the Demographic and Health Survey (DHS), Household Budget Survey (HBS), Health and Welfare Survey (HWS) of Thailand (Prakongsai, 2006), National Family Health Survey (NFHS) of India (Filmer and Pritchett, 1998; 2001), the World Bank's Living Standards Measurement Study (LSMS) and UNICEF's Multiple Indicator Cluster Survey (MICS), it is now possible to construct an asset index as an alternative measure of poverty inequalities. Earlier socio-economic measurement approaches dwelt on money metric measures such as the Gini coefficient, Purchasing Power Parity and gross domestic product (GDP) per capita. These so-called "direct" measures of socio-economic status (The World Bank, 2004; Balen *et al.*, 2010) are heavily based on income, consumption and financial assets such as savings and pensions.

Researchers such as Filmer and Pritchett (2001) and Filmer and Scott (2008) have established that an index based on a range of dichotomous variables of durable and semi-durable household assets and characteristics is more appropriate. This is particularly so in typical rural African settings, where the majority of the population do not depend on income earned from selling, wages from employment and labour and remittances (Prakongsai, 2006). According to Filmer and Pritchett (1998), an asset index constructed from principal components is of potential broad application. The study providing the basis of this paper applied these procedures in determining and classifying resilience levels based on a set of household assets, characteristics and livelihoods capitals.

The paper is structured in eight sections, including the introduction. Section 2 attempts to provide the rationale and the concept of resilience to food insecurity stresses and shocks. It underscores that resilience is a direct function of assets and endowments at the discretion of a household. Section 3 describes the dataset and methods used in the study. It shows the mathematical procedure for deriving the principal components and thus the asset-based resilience index. Section 4 elaborates the construction of the resilience index using z-scores of extracted principal components. Section 5 explains how the resilience profiles or categories are derived for each of the ten states of South Sudan. It extracts the states with weak resilience, with relatively moderate and with relatively high or strong resilience. Section 6 shows methods for validating the HRI by comparing it with a generated Household Wealth Index (a weighted household wealth profiles) and relating it to consumption expenditure. Section 7 presents a discussion of the findings of Sections 5 and 6. Finally, Section 8 makes a conclusion about the characteristic and strength of the resilience index.

2 WHY RESILIENCE?

In food security terms, resilience can be understood to be the ability of a household to "bounce back" after exposure to livelihood threats, shocks or stressors (Masten and Obradovic, 2006). Pasteur (2011) perceives resilience "as the capacity to endure shocks and stresses and bounce back". The shift in focus on resilience is exemplified by the need to control risk and prepare against the undesired effects of emergencies. Earlier focus of food security analysts was on measuring vulnerability. This means the approach was *post hoc* rather than *ante hoc*. A situation is determined after it has occurred. However, since strong or low resilience prevents or heightens vulnerability, there is a need to find ways to determine which categories or segments of a population have low or strong resilience. This makes a measure based on resilience an *ante-hoc* one.

Resilience is perceived to be a direct function of availability of household assets and livelihood capitals. The Department for International Development (DfID) (1999) presents a pentagon of livelihood capitals: human, natural, financial, physical and social. Taken together or individually, these livelihood capitals are said to influence livelihood outcomes as well as vulnerability. In retrospect, livelihood capitals can be determined by livelihood outcomes (sustainable use of natural resources, income, health and wellbeing) and vulnerability. This study is therefore motivated by this portrayal and that inequalities in levels of livelihood capitals can be a proxy to potential food insecurity risks. It is in this regard that PCA is used to mathematically determine inequalities in resilience levels based on household assets.

3 DATA AND METHODS

A dataset comprising a sample of 4 968 households was collected by the National Baseline Household Survey (NBHS) in early 2009 from all the ten states of South Sudan, to provide baseline information on poverty levels. The collected data covered a range of welfare dimensions such as housing conditions, education, access to healthcare, nutrition and food consumption. Sampling was based on a stratified two-stage sample selection with the 2008 Sudan Population and Housing Census providing the sampling frame. Census enumeration areas were the primary sampling units. A total of 44 census enumeration areas were drawn from each state, from which 528 households were drawn, giving a targeted sample size of 5 280 households.

The primary purpose of the NBHS was to report baseline information on poverty in South Sudan. The survey, in particular, aimed at providing poverty levels through collection of data leading to calculation of per capita consumption levels. It also aimed at providing information on welfare dimensions such as educational levels, access to health, housing conditions, and immunization, among others.

Table 1 presents some descriptive statistics of semi-durable and durable assets, housing conditions and characteristics in South Sudan in 2009. It also displays the scoring factors from the principal component analysis of the 33 variables.

Table 1 Per cent distribution of ownership of assets (South Sudan National Baseline Household Survey, 2009) (n = 4968)

Assets owned	Relative Frequency (%)	Mean	Standard Deviation	Scoring Factor*
Semi-durable Assets				
Motor vehicle	3.0	0.03	0.166	0.025
Motor cycle	4.8	0.05	0.210	0.040
Bicycle	29.0	0.29	0.454	0.106
Canoe/boat	1.4	0.01	0.118	0.003
Animal transport	2.0	0.02	0.139	-0.001
Television/sat. dishes	6.4	0.06	0.241	0.051
Radio	32.0	0.32	0.467	0.124
Phones	25.7	0.26	0.437	0.101
Computer	1.2	0.01	0.110	0.012
Refrigerator	1.7	0.02	0.123	0.017
Fan	2.2	0.02	0.145	0.021
Air conditioner	0.9	0.01	0.087	0.008
Sources of Income				
Crop farming	59.8	0.60	0.489	-0.045
Animal husbandry	5.2	0.05	0.221	-0.001
Wages and salaries	7.2	0.19	0.392	0.052
Business enterprise	5.8	0.06	0.233	0.003
Property income	1.1	0.01	0.104	0.002

Remittance	0.4	0.00	0.060	0.000
Pension	0.3	0.00	0.054	0.001
Aid	0.5	0.01	0.074	-0.002
Other source	7.2	0.07	0.262	-0.011
Housing characteristics				
Permanent dwelling	5.2	0.05	0.220	0.033
Semi-permanent dwelling	88.9	0.90	0.304	-0.029
Temporary dwelling	5.1	0.05	0.222	-0.004
Total number of rooms	---	2.51	1.518	1.512
Drinking water from pump/well	57.7	0.58	0.493	0.013
Drinking water from open source	36.3	0.37	0.482	-0.015
Drinking water from other source	5.1	0.05	0.223	0.002
Electricity for lighting	4.6	0.04	0.205	0.035
Cooking energy gas/electricity	0.4	0.00	0.065	0.004
Pit latrine	24.7	0.25	0.430	0.138
Flush toilet	1.1	0.01	0.100	0.007
No/other toilet	73.9	0.74	0.436	-0.145

* Scoring factors are composite variables which provide information about an individual's placement on the factor(s). The scoring factor coefficients are estimated using the Regression Method. They have a mean of zero and variance equals to the squared multiple correlation between the estimated factor scores and the true factor values. The scores may be correlated even when factors are orthogonal.

The interpretation of the information presented in the second column of Table 1 simply informs about the relative frequencies of household assets, endowments, conditions and livelihood capitals in the sample. This is the type of results most surveys produce. It explains how certain assets are owned by more households than others at the time of data collection. For example, we learn that more households (32%) owned radios while fewer (5.2%) had livestock. It cannot be known for certain that owning a radio is an indicator of wealth and, therefore, that a household is resilient to food insecurity. In other words, the percentages cannot be a proxy for wealth or showing a consumption pattern. From intuition, although there were far fewer households that had livestock (animal husbandry), they could be relatively well off or enjoying much higher resilience to food insecurity shock or strain than those owning a radio only. This is based on the simple fact that a household with a stock of animals could readily sell or consume from it than one owning only a radio or bicycle and therefore "bounce back" economically. Percentages are calculated taking into account that assets have equal weights, which in itself presents arbitrariness and lacks statistical strength.

Based on deduction by Filmer and Pritchett (2001), Principal Component Analysis (PCA) is used to construct an asset index that proxies for wealth and long-run socio-economic status; thus resilience to food insecurity shocks or stresses. PCA is a mathematical approach that derives the weights for each asset based on certain latent variables known as "Principal Components".

PCA is described as a simple non-parametric method that reduces a complex dataset to a lower dimension of variables. PCA is defined as a linear combination of optimally weighted observed variables. The procedure simply aims at reducing variables to a small number of components that account for most of the variation in a set of observed variables. The concept of PCA is built on the assumption that some of the observed variables are correlated with one another (O'Rourke *et al.* 2005).

The general form of the formula for computing the first principal component extracted from *p* variables is:

$$C_1 = b_{11}(X_1) + b_{12}(X_2) + \cdots + b_{1p}(X_p)$$

where C_1 is the subject's score on the first principal component, b_{1j} is the weight for observed variable *j* on the first component and X_j= the observed variable *j*. The strategy of PCA is to obtain total variation by standardising the observed variables. This is done by transforming each variable so that it has a mean of zero and a standard deviation of one. Then the variances of the observed variables are summed up such that each observed variable contributes one unit of variance to the total variance in the dataset. This makes the total variance in a PCA to always equal the number of observed variables being analysed.

Principal Components can be derived in more than one way. The simplest method is by finding the projection that maximizes the variance. Conceptually, the aim is to look for the projection with the smallest average (by squaring the mean) distance between the original vectors and their projections on to the principal components. This is the equivalent to maximizing the variance. The overriding assumption is that the data have been "centred", so that every one of the factor has mean 0.

If we write the standardized data in a matrix X, where rows are objects and columns are factors, then $X^T X = nV$, where V is the covariance matrix of the data. Two steps are essential in deriving the Principal Components:

First, minimizing the component residuals. This is done by looking for a one-dimensional projection. That is, we have p dimensional factor vectors, and we aim to project them on to a line through the origin. We can specify the line by a unit vector along it, $\bar{w}$, and then the projection of a data vector $\bar{x}_i$ on to the line is $\bar{x}_i . \bar{w}$ …, which is a scalar.

This is the distance of the projection from the origin; the actual coordinate in p-dimensional space is $(\bar{x}_i . \bar{w})\bar{w}$. The mean of the projections will be zero, because the mean of the vectors $\bar{x}_i$ is zero.

$$\frac{1}{n}\sum_{i=1}^{n}(\bar{x}_i . \bar{w})\bar{w} = \left(\left(\frac{1}{n}\sum_{i=1}^{n} x_i\right) . \bar{w}\right)\bar{w} \tag{1}$$

For any one vector, say $\bar{x}_i$, it is

$$\|\bar{x}_i - (\bar{w}.\bar{x}_i)\bar{w}\|^2 = \|\bar{x}_i\|^2 - 2(\bar{w}.\bar{x}_i)(\bar{w}.\bar{x}_i) + \|\bar{w}\|^2 \tag{2}$$

$$= \|\bar{x}_i\|^2 - 2(\bar{w}.\bar{x}_i)^2 + 1 \tag{3}$$

Adding all those residuals up across all the vectors:

$$RSS(\bar{w}) = \sum_{i=1}\|\bar{x}_i\|^2 - 2(\bar{w}.\bar{x}_i)^2 + 1 \tag{4}$$

$$= \left(n + \sum_{i=1}^{n}\|\bar{x}_i\|^2\right) - 2\sum_{i=1}^{n}(\bar{w}.\bar{x}_i)^2 \tag{5}$$

The term in the big parenthesis does not depend on $\bar{w}$, so it does not matter for trying to minimize the residual sum of squares. To make the RSS small, the term subtracted from it must be made big. That is, we maximize

$$\sum_{i=1}^{n}(\bar{w}.\bar{x}_i)^2$$

Similarly, since n doesn't depend on $\bar{w}$, we aim to maximize

$$\frac{1}{n}\sum_{i=1}^{n}(\bar{w}.\bar{x}_i)^2$$

which is the sample mean of $(\bar{w}.\bar{x}_i)^2$. The mean of the square is always equal to the square of the mean plus the variance:

$$\frac{1}{n}\sum_{i=1}^{n}(\bar{w}.\bar{x}_i)^2 = \left(\frac{1}{n}\bar{x}_i.\bar{w}\right)^2 + \mathrm{Var}[\bar{w}.\bar{x}_i] \tag{6}$$

We can see that the mean of the projections is zero. Therefore, minimizing the residual sum of squares is the equivalent of maximizing the variance of the projections. It should be noticed that, in general, we do not want to project onto just one vector, rather to multiple components. If those components are orthogonal and have the unit vectors $\bar{w}_1, \bar{w}_2 \cdots, \bar{w}_k$, then the image of x_i is its projection into the space of these vectors,

$$\sum_{j=1}^{k}(x_i.\bar{w}_i)\bar{w}_j$$

The mean of the projection on to each component is still zero.

The second step is to maximize the variance. If the n data vectors are stacked into an $n \times p$ matrix, i.e. X, then the projections are given by Xw, which is an $n \times 1$ matrix. The variance is

$$\sigma_{\bar{w}}^2 = \frac{1}{n}\sum_i (\bar{x}_i . \bar{w})^2 \tag{7}$$

$$= \frac{1}{n}(Xw)^T(Xw) \tag{8}$$

$$= \frac{1}{n} w^T X^T X w \tag{9}$$

$$= w^T \frac{w^T X w}{n} w \tag{10}$$

$$= w^T V w \tag{11}$$

Now, to choose a unit vector $\bar{w}$, we need to constrain the maximization. The constraint is that $\bar{w}.\bar{w}$ = 1, or $w^T w = 1$. This necessitates constrained optimization. The first step is to maximize the function f(w) (=$w^T V w$) given the equality constraint, g(w) = c , where $g(w) = w^T w$ and c = 1. Second step is to rearrange the constraint equation so that its right hand side is zero and g(w)-c=0. Next step is to add an extra variable, the Lagrange Multiplier λ to obtain our objective function u(w,λ) =f(w)+λ{g(w)-c}. We then differentiate with respect to both arguments and set the derivatives equal to zero.

$$\frac{\partial u}{\partial w} = 0 = \frac{\partial f}{\partial w} + \lambda \frac{\partial g}{\partial w} \tag{12}$$

$$\frac{\partial u}{\partial \lambda} = 0 = g(w) - c \tag{13}$$

It can be seen that the objective function is maximized with respect to λ to obtain the constraint equation, g(w)=c. Having satisfied the constraint, the new objective function equates to the old one. To derive our projection problem,

$$u = w^T V w - \lambda(w^T w - 1) \tag{14}$$

$$\frac{\partial u}{\partial w} = 2Vw - 2\lambda w = 0 \tag{15}$$

$$Vw = \lambda w \tag{16}$$

Thus, the desired vector w is an eigenvector of the covariance matrix V and the maximizing vector transforms to the vector associated with the largest eigenvalue λ.

V is a $p \times p$ matrix, so it will have p different eigenvectors. V is a covariance matrix, so it is symmetric, and in linear algebra terms, the eigenvectors must be orthogonal to one another. The second principal component is the direction with the most variance, which is orthogonal to the first principal component. Thus, the second principal component is the eigenvector of V corresponding to the second largest eigenvalue, and so on. Since it is orthogonal to the first eigenvector, their projections will be uncorrelated. In general, all principal components have projections which are correlated with each other. If k principal components are used, the weight matrix w will be a $p \times k$ matrix V. The eigenvalues will give the share of the total variance described by each component.

4 CONSTRUCTION OF THE ASSET INDEX

In this study, we examine data on the 33 variables as listed in Table 1. The values of each variable are dichotomized (transformed into binary) – except for the number of household members – to assign indicator values for each household. The SPSS Factor Analysis procedure is used to calculate z-scores by standardizing the indicator variables. This then leads to obtaining factor loadings and virtually the household index values. Finally, the first of the factors generated is then used as the wealth index. Principal Component Analysis (Table 2) used here, resulted in the first component extracted, although it explained only about 24% of the variability in the original 33 variables. As shown in Table 2, the first component carried far better weight (inertia) in the way of explaining variability than the subsequent extracted components. The first component has reasonably explained an adequate amount of variance and is thus selected as our Household Resilience Index (HRI).

Table 2 Variation explained by extracted Principal Components

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative
1	0.712	23.876	23.876
2	0.437	14.657	38.533
3	0.336	11.277	49.810
4	0.284	9.532	59.342
5	0.210	7.028	66.370
6	0.145	4.852	71.223
7	0.132	4.415	75.638
8	0.111	3.730	79.369
9	0.093	3.101	82.470

5 RESILIENCE PROFILES

The asset index proxies for household wealth but it is also the natural Household Resilience Index (HRI), as affordability of certain assets, the value of some livelihood capitals as well as presence of certain household characteristics and endowments may enable the household to become resilient in the face of food insecurity uncertainties and eventualities. The HRIs were grouped into quintiles to form five resilience categories: “*very weak*” (the household scores from 0 to the 20th percentile); “*weak*” (the household scores from the 21st to the 40th percentile), ‘moderate’ (the household scores above 40 to the 60th percentile); “*high*” (the household scores above 60 to the 80th percentile; and “strong” (household scoring from the 80th percentile and above).

As one of the two main aims of this paper is to determine resilience profiles in South Sudan, this was done by cross-matching the resilience levels against states on one hand, and against residential setting (i.e. urban and rural) on the other. It is, however, to be noted that as the country was in a post-conflict stage, following a two-decade civil war, living conditions between rural and urban populations were basically similar. Separate analysis carried out on the same dataset showed that both populations fared equally in most comparisons involving livelihood conditions, such as dependence on firewood for cooking energy, reliance on unsafe drinking water sources, non-use of modern toilet facilities and living in houses constructed from rudimentary materials. A cross-tabulation of the HRI levels by state (Table 3) showed clear disparities between states – reflecting the past and present reality in South Sudan.

Table 3 State resilience profiles in terms of Household Resilience Index (South Sudan, 2009)

	Household Resilience Index Quintiles (%)				
	Very Weak	Weak	Moderate	High	Strong
Upper Nile	16.5	19.2	23.5	19.9	20.9
Jonglei	22.6	37.7	20.0	14.5	5.2
Unity	23.3	23.1	22.5	18.3	12.8
Warap	32.6	23.9	21.3	14.4	7.8
Northern Bahr Al Ghazal	25.8	22.9	24.2	16.9	10.3
Western Bahr Al Ghazal	16.9	7.0	25.3	18.3	32.5
Lakes	27.0	12.4	26.4	20.9	13.2
Western Equatoria	6.3	2.9	8.4	43.4	39.0
Central Equatoria	10.2	10.0	14.2	23.2	42.5
Eastern Equatoria	39.5	25.9	12.1	9.8	12.7

Central Equatoria, Western Equatoria and Western Bahr Al Ghazal States were better off with over 30 per cent of their households indicative of ‘strong’ resilience to food insecurity shocks. In contrast, five states (Jonglei, Warap, Northern Bahr

Al Ghazal, Lakes and Eastern Equatoria) had a generalized "weak" resilience. One state, Upper Nile, had a generalized moderate resilience. These results were typical of known realities of the country at the time of the survey. The three states categorized as "strong" in term of resilience to food insecurity were characterized by generally agrarian populations, who largely depend on agriculture as their source of livelihood. They are also located in the "Green Belt" agro-ecological zone according to categorisation of livelihood profiles in South Sudan. As the name suggests, conditions in the Green Belt zones favour agricultural production and sustained livelihoods as the area is located a few latitude degrees above the Equator, have rich porous and iron-stone soil and a mean annual rainfall of 1 800mm per year (National Bureau of Statistics, 2010).

Another aspect that characterises these states is their occupation by relatively urbane, stable and educated populations compared with the seven other states. Juba, the current Capital City of South Sudan, combines as the administrative Capital of Central Equatoria State. Wau, the second largest town in South Sudan, is the administrative Capital of Western Bahr Al-Ghazal State with a more resident population, as it had remained under control of government forces during the two decade civil war of the undivided Sudan. The states with generalized "weak" resilience, on the contrary, had more rural and returning populations from internal displacement and exile. People were beginning to settle roughly three years into the return of peace in the country. These states were also relatively new and the population was predominantly comprised of pastoralists.

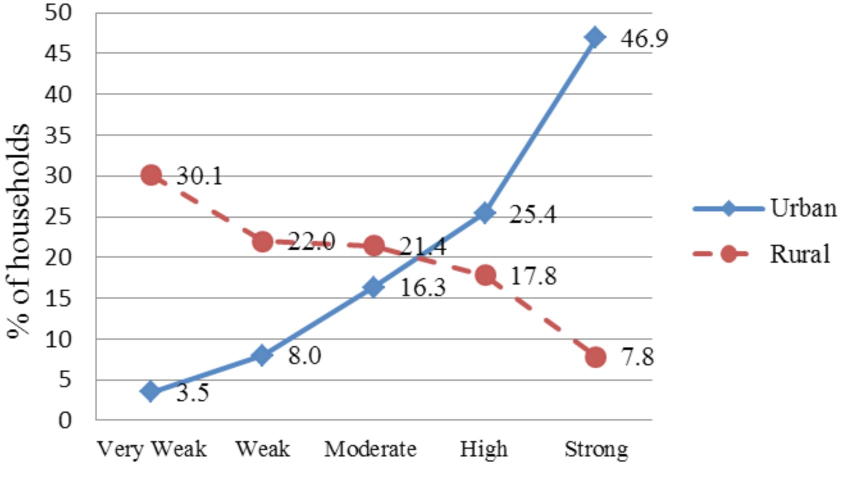

Figure 2: Levels of resilience by residential setting (South Sudan, 2009)

Classification of household resilience levels by geographical setting (Figure 2) showed clear disproportion between rural and urban households with regard to their resilience to food insecurity shocks and stresses. Whereas rural households in South Sudan were generally weak or moderate in their resilience levels, therefore facing more risk of vulnerability of food insecurity shocks, more urban households had generally 'stronger' resilience levels. This finding would have a bearing in planning for more rural and semi-rural development interventions.

6 VALIDATING THE HOUSEHOLD RESILIENCE INDEX

The HRI was validated by comparing it with the consumption-based Household Wealth Index generated during initial survey analysis conducted by the National Statistics Bureau (NBS) of South Sudan. Both the HRI and the HWI had a mean of 3.02 and 3.29, respectively (standard error of 0.009 for each). A test of association determined a strong relationship (Likelihood Ratio Test Chi-Square = 674.9 and DF=16 and p-value=0.000). The relationship between resilience and wealth can also be seen when the two variables are cross-tabulated as in Table 4.

Table 4 Household resilience levels by wealth index profiles (South Sudan, 2009)

Household Resilience Index Level	Wealth Index Quintiles (households)				
	Poorest	Poorer	Medium	Non-poor	Richer
Very Weak	23.1	24.4	19.9	17.4	15.2
Weak	25.6	20.0	21.7	16.7	16.0
Moderate	14.5	18.4	22.5	21.4	23.1
High	8.5	13.9	17.6	25.6	34.4
Strong	2.8	10.4	15.6	22.1	49.1

It is easy to note that "poorer" households were associated with "weaker" resilience to food insecurity while "richer" households in terms of consumption expenditure were associated with "stronger" resilience to food insecurity shocks. Whereas this result could be expected as "natural" occurrence, it establishes the HRI as a good determinant of how households would fare if exposed to vulnerability.

Scale values of the HRI were cast in a linear regression model with the values of log-transformed per capita consumption (expenditure) in real terms. The rationale for this measure was to determine whether resilience could determine consumption. The distribution of the Log-transformed per capita consumption is closer to normal than per capita consumption.

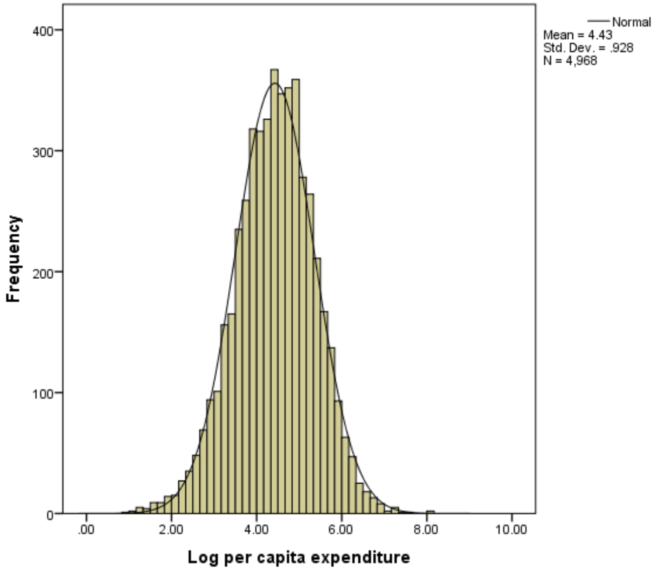

Figure 3: Distribution of the Log-transformed Per Capita Expenditure

A linear regression model assumes that there is a linear relationship between the dependent variable and each predictor. This relationship is described in the following formula.

$$y_i=b_0+b_1x_{i1}+\cdots+b_px_{ip}+\varepsilon_i y_i=b_0+b_1x_{i1}+\cdots+b_px_{ip}+\varepsilon_i \tag{1}$$

where $\boldsymbol{y_i}$ is the value of the i^{th} case of the dependent scale variable, p is the number of predictors, $\boldsymbol{b_j}$ is the value of the j^{th} coefficient, $j=0,\ldots,p$, x_{ij} is the value of the i^{th} case of the j^{th} predictor and $\boldsymbol{\varepsilon_i}$ is the error in the observed value for the i^{th} case.

One way to validate the HRI is to establish whether it is a good predictor of per capita consumption. In order to do this, a suitable model for prediction of a scale dependent variable by a scale predictor is a linear regression. Since there is only one predictor, which is the HRI, the above equation translates to a simple linear equation

$$y_i=b_0+b_1x_i+\varepsilon_i y_i=b_0+b_1x_i+\varepsilon_i \tag{2}$$

with b_0 being the intercept or the model predicted value of the dependent variable when the value of the predictor is equal to 0.

Figure 4 is an SPSS Output for prediction of Log-transformed per capita consumption by the HRI.

Table 1: Table 5 SPSS output of HRI prediction of per capita consumption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.373[a]	.139	.139	.86131

a. Predictors: (Constant), Resilience Index

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	594.650	1	594.650	801.569	.000[b]
	Residual	3684.062	4966	.742		
	Total	4278.712	4967			

a. Dependent Variable: Log per capita expenditure

b. Predictors: (Constant), Resilience Index

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.302	.013		331.013	.000
	Resilience Index	1.487	.053	.373	28.312	.000

a. Dependent Variable: Log per capita expenditure

The top part of the output in Table 5 shows that the regression model is poor in terms of the R-Square value. The regression analysis shows that the model explains only 14% of the variation in Log-transformed per capita consumption. The middle table gives the analysis of variance (ANOVA), which reports a significant F-statistic, indicating that using the linear regression model is better than inferences based on the estimated mean of the predictor variable. The bottom table shows the test of coefficients, which establishes the HRI as a very strong predictor of the wealth measure generated using household expenditure on consumption of essential goods and services. This part of the analysis also provides that prediction equation

(2) transforms to

$$\hat{y}_i = 4.302 + 1.487 * Resilience\ Index$$

where $\hat{y}_i$ is the predicted value of per capita consumption in household i.

7 DISCUSSION

7.1 PCA as good platform for constructing the HRI

The use of Principal Component Analysis in determining and profiling resilience levels was established to be sound both mathematically and statistically. Three important outcomes are generated from the application of the PCA technique: validity; reliability as a proxy measure and predictor of wealth; and determination and profiling of "preparedness" of geographical entities against food unfavourable conditions causing food insecurity.

As regards its validity product, the Household Resilience Index, generated by reducing 33 variables into one component, which carries a substantive amount of the variance of those variables, was adequately representative of the weight of assets and housing characteristics. The large number of variables, especially those from related questions on availability of semi-durable assets, meant that variability spread out considerably, resulting in the first two extracted components accounting for a relatively low percentage of the variance (38.5 per cent). Moreover, most of the variables on semi-durable assets contained "no" responses, as most of the populations did not have them. As South Sudan was barely two years old after two decades of civil war, the bulk of the population was in the process of settling down. Only a small segment of the population had assets such as motor vehicles, motor boats, televisions, air conditioners and refrigerators – these assets are typically associated with a settled population.

The relative frequencies in Table 1 clearly showed stark deprivation from assets associated with wealth of families such as motor vehicle, use of electricity, flush toilets, having air conditioners and using gas or electricity as source of cooking energy. At the time of the baseline survey, it was clear that only a small proportion of households (0.9 to 3 per cent) had these types of assets and what characterised their livelihood. Inclusion of these variables in the analysis is responsible for the low variability explained by the first extracted component, as shown in Table 2. Indications of the variance accounted for by the extracted components are very low for these variables. This occurrence is known as "communalities" in PCA parlance. A solution to this problem could be to discard some of the variables known to have low frequencies from the analysis. However, this being a baseline study, it was seen worthwhile leaving the variables for future comparative analysis.

Studies that used PCA to construct an asset-based index used a lower range of variables. Sahn and Stifel (2003) deployed 11 variables in their comparison of socioeconomic welfare in 12 developing countries. Even so, a considerable number of variables had low scoring coefficients or weights from the first extracted principal component, reflecting a large body of respondents reporting not having those assets or attributes. In their construction of an asset index for measuring asset accumulation in Ecuador, Moser and Felton (2007) conducted desegregated or structured analysis based on four livelihood capitals: physical (housing conditions and consumer durables); financial or productive capital (labour security, productive capital and transfer/rental income); human (mainly level of education attained); and social (house and community).

The second outcome of the analysis is that it has been established that the HRI is able to predict and associate with purchasing power or monetary wealth represented in per capita consumption. Table 4 clearly demonstrates the association of the HRI and the spending power in terms of consumption per capita. Stronger resilience manifests itself in the relatively wealthier households. Conversely, weaker resilience is a preserve of poorer households or those that spent less on food and other life necessities.

As regards its discriminating ability, the HRI is found to do well in profiling resilience to food insecurity adversaries by geographical or demographic characteristics. In this study we profiled the ten states of South Sudan according to their resilience levels in 2009. We determined that the states of Warrap, Northern Bahr Al-Ghazal, Jonglei and Eastern Equatoria were characterised by weak to very weak resilience to food insecurity in as far as they had generally and commonly a lower asset base and poorer housing conditions than the rest of the states. Lakes State, Unity State and Upper Nile State had what could be termed “generalised moderate” resilience to food insecurity uncertainties. Both the “worse” or “moderate” states could be described in food security early warning jargons as “alert” or “watch” and, therefore, would need adequate preparatory measures for safeguarding against the eventuality of food insecurity causes, such as sudden market price increases, crop failure and low food commodity stock, supply road closure or others. On the other side of the scale, the states of Western Equatoria, Central Equatoria and Western Bahr Al-Ghazal, in that order, enjoyed relatively stronger resilience levels in 2009. As explained by their common advantage of favourable geographical and demographic conditions, these states would not be regarded as “intervention areas” by food security mitigating and management organisations.

The rationale of opting for a measure of resilience is anchored in the fact that populations with low resilience become easily vulnerable to food insecurity calamities. Populations lacking in a combination of certain livelihood capitals, semi-durable and durable assets conceptually or naturally are low resilient to food insecurity eventualities and are, therefore, more vulnerable. Traditional measures of food security are largely based on vulnerability and more specifically on food consumption, micronutrient intake (e.g. calorie intake, dietary diversity and food consumption access) and anthropometrics in nutrition studies. Such studies are retrospective in that they examine data of events that have already occurred. A study for measuring resilience is, on the other hand, prospective, as it examines how the household or the area of study will fare in the future when certain factors prevail. It was for this reason that this study got its motivation.

7.2 Distinguishing merits of the HRI

As food insecurity has proven to be an increasing problem of major concern in Africa, especially in settings where poverty is more rooted, there is a need to explore pragmatic measures that prompt for appropriate and decisive action to prevent it from plunging a population into life threatening situations. In the case that certain population groups are affected by chronic or structured food insecurity, there is a need for a measure that indicates how well prepared or how resilient the population will be. As explained in the preceding paragraph, the Household Resilience Index explored in this study provides a reasonable measure for ascertaining the level of resilience of households or the settings where they exist, such as states, counties or other localities. The HRI can be merited on six fairly good attributes.

The first attribute of the index is that it is a single summative measure. Being a composite indicator based on weights of several variables, it serves as a universal measure of livelihood attributes of a population group. Whereas previous studies using similar approaches explored the asset-based index as socio-economic welfare indicator, this study treats it as a measure of how resilient individual households, or geographically/demographically grouped households, can potentially withstand the eventualities of food insecurity.

The second attribute of the index is that it has been established as a good alternative to money metrics based on income or consumption expenditure data. Comparative analysis explored in this study clearly demonstrates that the HRI can cater for the absence of the money metric-derived Wealth Index. Considerable arguments have been presented that welfare measures based on monetary values of income or consumption variables present certain amount of biases attributable to recall, inaccuracies and others. Welfare and poverty researchers such as Gwatkin *et al.* (2000) argue that income measures lend themselves to practical difficulties such as reluctance of informers to disclose how much income they have earned, lack of record keeping of money spent on consumption and many others. Liverpool and Winter-Nelson (2010: 3) argue that consumption data can be affected by endogenous factors such as seasonality and weather conditions, and therefore could not be a good measure of welfare.

The third advantage of the HRI is its ability to predict the probability of socio-economic conditions such as wealth, food consumption levels, among others. The index can inform vulnerability analysts to plan long-term interventions to limit adverse effects of conditions that threaten the livelihood and survival of a population. Furthermore, the index can predict or explain the state of socioeconomic deprivation and livelihood disparities among different population groups. Sahn and Stifel (2003) conclude that the index based on assets and livelihood endowments of households is a valid predictor of crucial manifestations of poverty such as child health and malnutrition. Filmer and Pritchett (2001) find the asset index to be as “reliable” a predictor of school enrolment as a measure based on consumption.

As discussed in the foregoing section, the HRI has a fourth worth in profiling resilience by geographical or demographic setting. If the analysis were carried out immediately after the survey in 2009, it could act as an early warning on which states of South Sudan needed early preparedness against the eventuality of food insecurity shocks. The states that show very low or weak resilience can then be mapped out with red colour in order to invoke commitments and actions for early preparedness measures.

The fifth distinguishing characteristic of the HRI is that it is simple and easy to derive and interpret. Simplicity of the measure arises both in the raw data used in the analysis as well as the method used. Filmer and Scott (2008) observe that the data used to construct the index are simple to collect and frequently available. Moser and Felton (2007) describe the measure based on PCA as “relatively easy to compute and understand”. Morris *et al*. (1999) put the PCA-based index in the category of simple measures that proxy for wealth indexes.

The sixth distinctive advantage of the index is durability. Since the index is based on semi-durable and durable assets, property owned (e.g. farmland, animal husbandry and other fixed assets) and households’ livelihood attributes (type of dwelling, sleeping rooms, source of lighting and cooking energy, etc.), it proves to be a medium to long-term measure and, therefore, prompts for interventions with long-term goals and targets. It is important to note that the index is constructed using data that are always readily available in databanks of most national statistical agencies of developing countries. Datasets from national household budget surveys, demographic and health surveys and other socioeconomic status surveys are collected on a regular basis by statistical agencies. Survey questionnaires include items on different livelihood aspects as outlined in Table 1.

8 CONCLUSION

Drawing from the elaborated six advantages of the HRI, it is paramount to derive a conclusion that the HRI can withstand the test of being a reliable early warning measure for planning food security interventions, especially in chronically food insecure settings such as some livelihood zones in South Sudan.

Another important aspect to consider is that the index, based on a reasonably large sample size of 4 968 households, which is representative of all ten states of South Sudan, has inherent statistical reliability, as its association with another livelihood measure – household wealth proxied by consumption data – has been determined to be strong.

It has also been established that, as recognised by other researchers who constructed a socioeconomic measure (index) based on assets, the Principal Component Analysis technique provides a mathematically and statistically sound platform for constructing the HRI. One challenge that could be encountered in constructing the HRI is the range of asset and livelihood capital-based variables. In the case of South Sudan, the index could probably become more robust if fewer variables (say, less than 30) were used that typically reflect the reality at the time of the survey. We could not be certain whether assets that were largely owned by a small section of the population at the time, such as television, refrigerators, fans and motor vehicles, should be included in the study. The reality at the time of data collection was that a substantial proportion of the population of South Sudan was still settling down and most of the people had no electricity or modernised assets. This could present a drawback in the study findings.

Nevertheless, it is important to consider that the crux of the study is to present a procedure that might help in determining inequalities in a resilience of population groups to food insecurity uncertainties. This has been done as discussed above. The HRI has been established to a large degree as a prospective measure of potential risk and easy to determine using readily available data from periodical livelihood-related surveys. We, therefore, propose the adoption of the HRI for use in determining, mapping and profiling inequalities in resilience and potential vulnerability to food insecurity risk factors, as well as unveiling evidence for triggering early preparedness.

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