Food and Agriculture Organization of the United Nations

ANALYSING RESILIENCE FOR BETTER TARGETING AND ACTION

RIMA-II

RESILIENCE INDEX MEASUREMENT AND ANALYSIS - II

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ACRONYMS

ABS	Access to Basic Services
AC	Adaptive Capacity
AST	Assets
CFI	Comparative Fit Index
DDI	Dietary Diversity Index
DFID	Department for International Development
FA	Factor Analysis
FAO	Food and Agriculture Organization of the United Nations
FCS	Food Consumption Score
GIS	Geographic Information Systems
GMM	Generalized Method of Moments
HDDS	Household Dietary Diversity Score
HH	Household Head
IGA	Income Generating Activities
IV	Instrumental Variable
LDC	Less Developed Countries
LHS	Left Hand Side
LSMS-ISA	Living Standards Measurement Study - Integrated Surveys on Agriculture
MIMIC	Multiple Indicators Multiple Causes
ML	Maximum Likelihood
MUAC	Mid-Upper Arm Circumference
OLS	Ordinary Least Square
PCA	Principal Components Analysis
RAP	Resilience Analysis and Policies
RCI	Resilience Capacity Index
RHS	Right Hand Side
RIGA	Rural Income Generating Activities
RIMA	Resilience Index Measurement and Analysis
RM-TWG	Resilience Measurement Technical Working Group
RMSEA	Root Mean Square Error Approximation

Acronyms

RSM	Resilience Structure Matrix
S	Sensitivity
SEM	Structural Equation Model
SES	Socio-Ecological System
SRMR	Standardized Root Mean Square Residual
SSN	Social Safety Nets
TLI	Tucker-Lewis Index
UBoS	Uganda Bureau of Statistics
UN	United Nations
UNHS	Uganda National Household Survey
UNICEF	United Nations Children's Emergency Fund
UNPS	Uganda National Panel Survey
WFP	World Food Programme

1 INTRODUCTION

This chapter introduces the concept of resilience in the economic environment, starting from the idea given by Béné (2013). It goes through the relative big literature ending up with the most recent concept of resilience given by the Resilience Measurement Technical Working Group. Given the latent nature of resilience, the concept of direct (or descriptive) and indirect (or inferential) measure, developed recently by the RAP team, is introduced, as well as the innovation of RIMA-II in building a bridge between the direct and indirect measure.

Numerous United Nations (UN) agencies, development, governmental and non-governmental organizations and donors look to resilience as a promising concept for understanding how households cope with shocks and stressors, trying to streamline its use in their regular programming, targeting and measurement activities.[1] One of the most compelling features of a resilience approach is identification of how the combined effect of climate changes, economic forces and social conditions has increased the frequency and severity of risk exposure among vulnerable populations.

As a result, many attempts at measuring resilience have been proposed over recent years, using both quantitative and qualitative approaches. The Food and Agriculture Organization (FAO) of the United Nations has a long record of experience in this, being the first organization to adopt the concept of resilience in a food security context (Pingali *et al.*, 2005) and in 2008 proposed an econometric approach, the RIMA, for measuring resilience (Alinovi *et al.*, 2008). More recently, others proposed alternative approaches to measure resilience (Frankenberger *et al.*, 2012; Vaitla *et al.*, 2012).

Every measurement strategy has to be built upon a definition of resilience. Most approaches, tools and methods proposed in the literature to measure resilience reflect the diversity of disciplines and sectors that have appropriated the term (Béné, 2013). RIMA was created using the following definition of resilience: "The capacity of a household to bounce back to a previous level of well-being (for instance food security) after a shock".

[1] Policy documents explicitly referring to or attempts to use resilience.

However, it reflects the definition that has been recently adopted by the Resilience Measurement Technical Working Group[2] (RM-TWG) where resilience was defined as "a capacity that ensures stressors and shocks do not have long-lasting adverse development consequences".

Resilience is not easily measured, and given this constraint, it is necessary to look at resilience using a proxy measure, of which there are two, one direct and the other indirect.

A direct (or descriptive) measure of resilience aims at targeting and ranking households. Its main purpose is to identify those households less likely to resist a shock, and thus functions as a descriptive tool. In this paper a direct measure of resilience was obtained using a latent variable model, termed MIMIC (Multiple Indicators Multiple Causes). By definition and statistical properties, this approach employs resilience capacity and structure as a mean for comparison within a dataset. The direct measure looks at capacity and structure at a specific moment in time. There is also the possibility to look at how capacity and structure evolve over time.

An indirect (or inferential) measure of resilience looks at its main determinants. There is a range of resilience indicators that can be employed, such as speed of recovery and extent of loss or recovery. The indirect measure allows statistical inference to be made that ultimately translates into clear and sound policy indications and can be adopted for predicting a dynamic perspective of resilience.

An ideal bridge between direct and indirect measures of resilience is represented by the Resilience Capacity Index (RCI), which can be employed as to predict food security. This approach was pioneered by Ciani and Romano (2011) and was further tested by d'Errico and Di Giuseppe (2016) and Kozlowska *et al.* (2015).

RIMA-II therefore represents a package that includes the two approaches, direct and indirect. The direct approach measures the RCI and the Resilience Structure Matrix (RSM). The indirect approach looks at the determinants of food security loss and recovery.

This document presents the new estimation procedure, RIMA-II, for gauging household resilience to food insecurity and begins by summarizing the RIMA experience in Section 2, then discusses choice of an appropriate unit of analysis (Section 3) and presents the data employed for the analysis in Section 4. RIMA-II is presented in Section 5, direct measurement is explained in Section 5.1. The capacity of the RCI as a predictor of food security is presented in Section 5.2, while the indirect measure is explained in Section 5.3. Section 6 represents the conclusion of the work.

[2] Further information are available at at www.fsincop.net/topics/resilience-measurement/technical-working-group.

2 RESILIENCE INDEX MEASUREMENT AND ANALYSIS (RIMA) EXPERIENCE

This chapter introduces the new Resilience Index Measurement and Analysis II (RIMA-II) methodology, presenting the area of improvement with respect to the previous methodologies. Detailed information on the pillars construction is also provided.

Early empirical applications of FAO RIMA (Alinovi *et al.*, 2008; Alinovi *et al.*, 2010) adopted two-stage Factor Analysis (FA) with Bartlett's prediction technique. In the first step resilience pillars were estimated through FA of observable variables and RCI was then estimated through FA of the pillars (for pillars aggregation process see Annex II).

The last generation of RIMA applications (d'Errico *et al.*, 2015a; FAO *et al.*, 2014) employed factor analysis at the first stage and then estimated RCI by adopting a Structural Equation Model (SEM) at the second stage (Costello *et al.*, 2005; Scott, 1966). Root Mean Square Error of Approximation (RMSEA), Chi-squared tests, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI) and Standardized Root Mean Square Residual (SRMR) were estimated to evaluate goodness-of-fit and, ultimately, correlation between residual errors.

A modified RIMA-I approach was recently employed as a predictor of well-being variation over time (Ciani and Romano, 2011) to estimate rural household resilience in Nicaragua and the capacity of an RCI to predict future food consumption. In Burkina Faso Kozlowska *et al.* (2015) employed RIMA-I following the approach of Dang *et al.* (2014) and Moffit (1993) to estimate the RCI from synthetic panel data Ordinary Least Square (OLS) and Instrumental Variable (IV) adopted. D'Errico and Di Giuseppe (2016) used real panel data from Uganda to estimate resilience dynamics (fixed and random effect models adopted). Finally, in Mali, d'Errico *et al.* (2015b) estimated RIMA to determine, through regression analysis, the effect of resilience on a well-being indicator from the Mali Bureau of Statistics.

2.1 AREAS OF IMPROVEMENT

The major limitation of RIMA-I was when addressing dynamic analysis with the RCI. Causal inference with latent variable models presents structural limitations. Although the possibility of making causal inference with latent models is recognized in Von Eye and Clogg (1994), typically such models are adopted for descriptive purposes. Furthermore, explanation and interpretation of the model's results can be problematic for those not familiar with the accompanying literature. RIMA-II proposes an indirect measure of resilience that adopts regression analysis and, consequently, allows causal inference.

Another recurrent limitation of latent variable models is endogeneity (i.e. the risk of causality between independent and dependent variables). RIMA-I could not be employed, for example, to determine the causal effect of an increase or decrease in resilience of food security because food expenditure was one of the variables of the Income and Food Access pillar. Moreover, analysis of shocks was impractical because they were also included in the estimation procedure. Therefore, both shocks and food security indicators were removed during the estimation procedure for direct and indirect measurement of resilience.

There are other limitations that are not addressed in this note, such as those associated with risk management. Households choose between asset smoothing and consumption smoothing as a strategy to cope with shocks in order to maintain long-term levels of food consumption and well-being. This decision significantly affects the capacity to meet future minimum food security requirements. Unfortunately, this latter aspect is not measurable to date. Scarcity of high quality and extensive time series data affects capacity to study (and learn from) such a coping strategy.

Similarly, there are additional limitations that can not be addressed without extensive time series data. For instance, the effects on resilience of long-term and short-term interventions differ (e.g. education), shocks mitigating policies can have immediate or long-term effects (e.g. food for work projects) and shocks can devastate or simply compromise household capacity depending on their number, magnitude and frequency. Valid datasets are needed to study these aspects that are currently ignored.

2.2 CONCEPTUAL FRAMEWORK

Resilience is an intrinsically dynamic concept that exhibits complex and far-from-equilibrium dynamics (Levin *et al.*, 1998) and as such requires a dynamic analytical framework. Small perturbations in a non-linear system can be magnified and lead to qualitatively unexpected behaviours at more macroscopic levels (Levin *et al.*, 1998).[3] Barrett *et al.* (2014) presented a good representation of non-linear expected well-being dynamics with multiple stable states. Households are affected by both positive and negative shocks. A high food price shock could have a negative effect on some households but could translate into a positive effect for producers and sellers. Ideally both effects should be captured in order to analyse the long-term effect of shocks and related coping strategies. In the case of consumption or asset smoothing strategies, reducing short-term consumption could become a positive coping strategy if it fits into the long-term perspective of investments.[4]

A broad distinction between immediate needs and intervention over the long term places the resilience discussion in the debate between emergency and development response mechanisms. This has a number of implications for measurement. Firstly, a long time frame is needed to ensure response mechanisms are effective. It is likely that the well-being indicators fluctuate during the short and medium term and finally stabilize over the long term. Secondly, when a shock occurs there may be long-lasting consequences for household assets and livelihoods (for instance, selling assets is a typical strategy but its impact on household livelihood depends on the assets sold). Thirdly, a distinction needs to be made in terms of long-term and short-term interventions. Policies aiming at increasing resilience or minimizing reduction in well-being connected with a shock can have immediate effect (food for work projects, transfer mechanisms) or long-term implications (typically education).

[3] However, lack of appropriate data currently reduces the possibility of exploring these aspects.

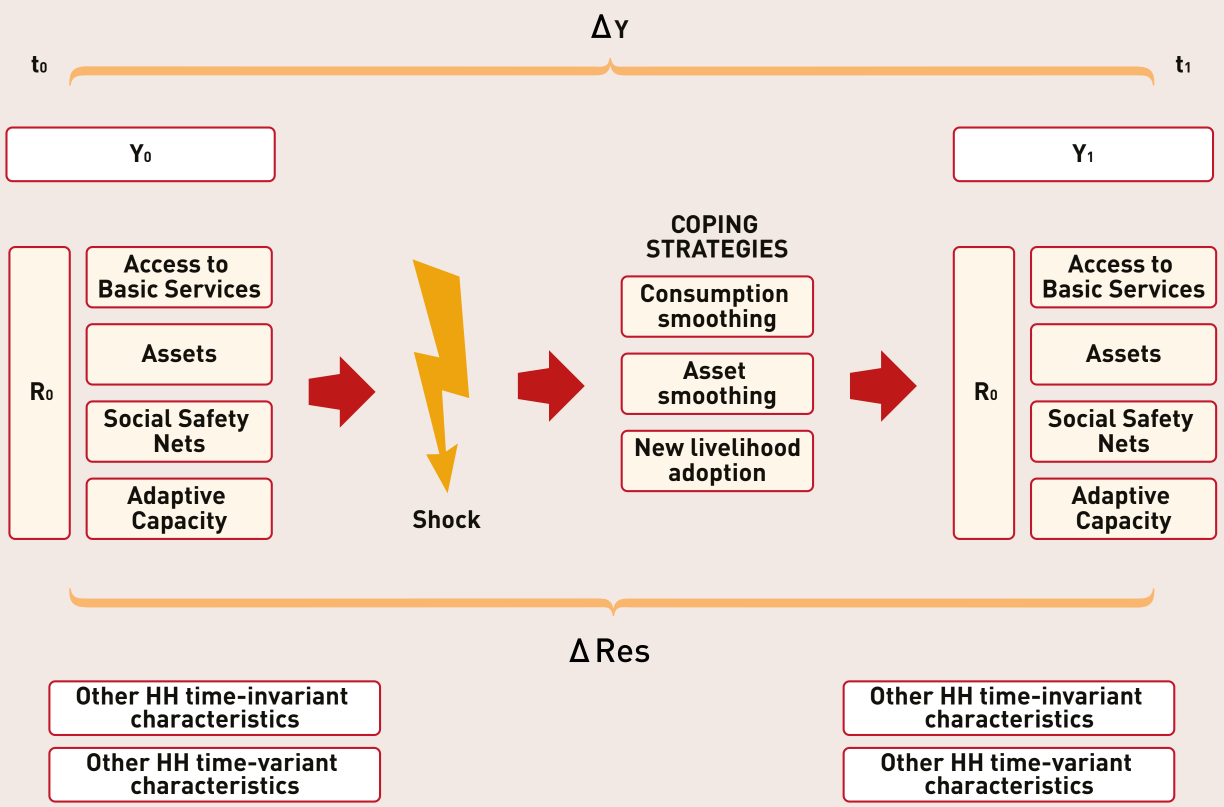
[4] One can focus on capital accumulation in a high food price moment, investing in food production in order to promote a longer period of well-being.

A conceptual framework for resilience measurement has to capture all possible pathways to well-being in the face of shocks. Figure 1 describes what happens to an household well-being when a shock occurs and resilience mechanisms are activated. This analytical framework is based on classic psychometric theories (Crocker and Algina, 1986; Cronbach and Meehl, 1955; Nunnally and Bernstein, 1994) as well as on more modern measurement references (Preacher *et al.*, 2013); it is also the natural evolution of the conceptual framework elaborated by Alinovi *et al.* (2008).

Y_0 (e.g. food security at time 0) is obtained through a set of time-variant and time-invariant characteristics, a number of pillars contributing to household resilience capacity. When a shock occurs, a series of coping strategies is activated, principally consumption smoothing, assets smoothing and adoption of new livelihood strategies. Household resilience contributes to these absorptive, coping and transformative capacities in an attempt to bounce back to the previous state of well-being. This can result (over the long-term) in an increase or decrease in Y. Any change in Y has an effect on resilience capacity and, consequently, can limit future capacity to react to shocks.

Figure 1 represents the conceptual framework employed as a basis for the estimation of RIMA-II.

Figure 1. **Resilience conceptual framework**



2.3 RESILIENCE PILLARS

Building (and measuring) household resilience to food insecurity by definition requires a multidimensional approach. The question concerns which pillars to include in Figure 1. This can only be determined by investigating the resilience building strategy.

In Pingali *et al.* (2005) resilience building strategies were based on the following principles:

- strengthening diversity;
- rebuilding local institutions and traditional support networks;
- reinforcing local knowledge; and
- building on household ability to adapt and reorganize.

Alinovi *et al.* (2008) emphasized household capacity to resist and absorb a shock. They stated that the ability of a household to adapt to new scenarios depends on the options available to that household to make a living, such as access to assets, income-generating activities, public services, formal and informal social safety nets, institutional environment and resistance capacity. These are *ex ante* conditions that pre-exist a shock. They fit into two broad categories: a so-termed ecological component (for the basic resources: the natural and human resources a household has at its disposal) and an economic one (for socio-economic and transformative components: the capacity the household has to transform, adapt and create).

Vaitla *et al.* (2012) adopted a "livelihood change" approach, consisting of modelling the pre-existing conditions with assets, natural resources, physical assets, financial assets and human and social capital. These are the fundamentals elements of resilience, which after interaction in a vulnerability context (factors outside human control) and an institutional context (human factors outside the household's control) enable households to react to a shock.

Ellis (2000) defined a livelihood as consisting of "[...] the assets (natural, physical, human, financial and social capital), the activities, and the access to these (mediated by institutions and social relations) that together determine the living gained by the individual or household". Although livelihood and income are not synonymous, they are nevertheless inseparably connected because income "at a given point in time is the most direct and measurable outcome of the livelihood process". The livelihood approach emphasizes the role of household resources as determinants of activities and highlights the link among assets, activities and incomes. Households allocate resources to activities subject to factors external to the household, which generate outcomes that meet the objectives. The activities and the income generated affect the future stock of resources available to the household. The total household income is the aggregate measure of the outcome of all the activities in which the household is engaged.[5]

In Frankenberger *et al.* (2012) the conceptual framework for resilience addresses the underlying causes (e.g. institutional, structural, socio-economic and environmental) that contribute to vulnerability and seeks to understand and address how long-term trends (e.g. climate change, economic, socio-political and environment factors) affect livelihood security and exposure to risk, which results either in increased vulnerability or increased adaptive capacity over time. In terms of measurement, many aspects are included: physical, political, social, human, natural, financial assets, institutions and livelihood strategies.

A Department for International Development (DFID) paper (2011) isolated four elements for a resilience framework: context, disturbance, capacity and reaction.[6] In terms of measuring the resilience capacity, it is therefore necessary to look at DFID determinants of capacity and reactions. Capacity is determined by exposure to risk, sensitivity and adaptive capacity.

[5] It depends on how many income generating activities households are engaged in. In the context of income diversification, various studies highlight the importance of risk. Studies by de Janvry *et al.* (1991) and Kinsey *et al.* (1998) indicate that income diversification is positively correlated with an increased ability to cope with shocks. Diversification is a way households insure themselves against the occurrence of such shocks.

[6] Context is more connected with answering the question "resilience of what?" Disturbance, in turn, is the shock element of the resilience analysis and as such will be treated in the appropriate section.

Building factors are assets and resources can be social, human, technological, physical, economic, financial, environmental, natural and political.

Barrett and Constas (2014) were more interested in the dynamics of well-being than in the resilience estimation itself, but clearly mentioned that conditional expectation functions of well-being arise from individual and collective choices subject to constraints imposed by human institutions (laws and norms), resource availability (money and time) and nature.

All the above-mentioned approaches seem to originate from the asset-income-output causal chain suggested by Dercon (2001): "Households and individuals have assets, such as labour, human capital physical capital, social capital, commons and public goods at their disposal to make a living. Assets are used to generate income in various forms, including earnings and return to assets, sale of assets, transfers and remittances". Under these circumstances, all the major approaches to resilience measurements seem to recognize (implicitly or explicitly) the relevance of two broad areas of indicator: a natural base and an enabling capacity for adaptation and transformation.

These two sets of indicators resemble two definitions of resilience: ecological resilience, which can be measured as the magnitude of the perturbation that can be absorbed by the system before falling from one state to a lower one (Gallopin, 2006) and engineering resilience, that can be measured as the speed at which the system returns to the stable point or trajectory following a perturbation (Pimm, 1984; Holling, 1996).

The most credited and recent description of core components of resilience seems to be that in Béné *et al.* (2012). The authors expand the framework proposed by Walker *et al.* (2004) and propose absorptive, adaptive, and transformative capacity as the three structuring elements of an analytical framework for resilience analysis. This description has been also recently supported by the FSIN Resilience Measurement Technical Working Group (2014a and 2014b). FAO acknowledge and deem this description as theoretically valid. However, FAO's mandate and the practical application that a resilience measurement tool is supposed to accomplish, requires a more practical classification which can eventually serve as basic for deep analysis. In this sense, RIMA-II remains consistent with the original FAO's analytical framework (FAO, 2012), although some innovation are introduced as aforementioned.

Fundamental pillars of resilience are, therefore:

- Access to Basic Services;
- Assets;
- Social Safety Nets;
- Sensitivity; and
- Adaptive Capacity.

Other pillars could be included, such as aspects of climate change and institutional environment.[7] Moving from the conceptual framework to an analytical framework requires the definition and identification of the most accurate indicators for each pillar.

The procedure follows two general approaches, one based on a theoretical understanding of relationships and one based on statistical relationships (Adger *et al.*, 2004) and, as a consequence, the indicators could theoretically be valid but be statistically irrelevant or not usable.

The following sections discuss the most important indicators adopted for each pillar.

[7] Provided that no single representation of resilience can be exhaustive, but each is rather a proxy of the actual (abstract and not well defined) resilience, it is therefore necessary to accept a certain degree of tolerance.

2.3.1 Access to Basic Services (ABS)

Having ABS, such as schools, health centres, water, electricity and nearby markets, is a fundamental aspect of resilience for three main reasons. First, the capacity of generating income from assets, a key dimension of resilience, is constrained by access to market institutions, as well as non-market ones, public service provision and public policy (Dercon *et al.*, 2004). For example, crop sales at the farm-gate or district market can result in very different revenues for farmer households. Furthermore, the density of the road network influences not only access to markets, but also the efficacy of aid distribution in response to disasters (Adger *et al.*, 2004). Recent evidence supports the association between access to basic services before a disaster and the rate of recovery after a disaster (Khan, 2014). Second, ABS plays a key role in determining the risk exposure of households and communities. For example, "risk of illness is often closely related to particular environmental risks, linked to inadequate waste disposal, water supplies, and sanitation" (Dercon *et al.*, 2004). These risks are also very relevant in urban areas (Moser, 1998). Third, the relationships between state and civil society assume a relevant role in adaptation. Inefficient state institutions are likely to neglect adequate healthcare, housing and sanitation, leading to inefficient responses to shocks. In contrast, democracy and accountability push governments to manage risks and shocks adequately in order to be re-elected (Adger *et al.*, 2004).

ABS refers to both access to services and the quality of access and services. Consequently, there are two categories of indicators to proxy ABS. In terms of access, following the literature using household surveys, see for example (Aguero *et al.*, 2007), services to be considered are schools, hospitals and other health services, markets, stores, paved roads, safe houses and water and waste disposal systems.

On the other hand, a proxy for the quality of access can be the monetary cost of access to services. According to Adger *et al.* (2004), the increase in health and education costs is an important process that positively affects household vulnerability. Subjective indicators can also be employed, such as public perception of the quality of services and security in the community where the household is located.

2.3.2 Assets (AST)

There is an extensive literature on the effects of shocks on household living conditions and on the coping strategies adopted to overcome them. Studies investigated whether specific risk-coping strategies were responsive to shocks (Pan, 2007); (Udry, 1995); (Rosenzweig and Wolpin, 1993); (McPeak, 2004); (Kochar, 1999), or whether consumption could be smoothed in relation to transitory income changes (Paxson, 1992; Gertler and Gruber, 2002; Kazianga and Udry, 2004; Jalan and Ravallion, 1997).

One of the most direct (and popular) measures of standard of living is income. In general terms, income refers to the earnings from productive activities and current transfers and can be seen as comprising claims on goods and services by individuals or households. In other words, income permits people to obtain goods and services. Income is also a determining factor when dealing with shocks (Dercon, 2002). Income is the starting point in coping with shocks, considering that a higher income could lead to greater savings, which could be important during the post-shock recovering phase.

When analysing household response to shocks, a central issue to be considered is not only income, but also the role of assets. When they contribute directly to the income generation process (productive assets), shocks can have different consequences and lead to different behaviours, i.e. selling assets or slowing down asset accumulation could have important implications for future income generation. Transitory shocks can have long-term consequences when income loss leads to changes in asset investment decisions. Households might reduce their consumption to preserve their assets (this is the case of asset smoothing) (Barrett and Carter, 2005; Zimmerman and Carter, 2003), or they can sell assets to protect consumption (consumption smoothing). According to Hoddinott (2006), the probability of selling assets (e.g. animals) in the face of a negative-income shock depends on the prior level of assets.

As a result, income and assets should be part of the resilience pillars. However, the inclusion of income in the estimation model could lead to some problems. Given that pillars are constructed using factor analysis, where correlation is very important, collinearity problems can arise when entering income as one of the pillars because of its strong relationship with them.

In addition to multicollinearity problems, income measurement limitations are always present (Box 1).

Box 1. Dealing with income issues

It is not always easy to calculate income. Income data are difficult to collect and income is only received intermittently, whereas, for example, consumption is smoothed over time. Consumption over a week period recall, or a month period recall, can provide a good indication of the level of consumption during a full year. Measured income over the same period is most likely to be an inaccurate measure of income for a full year. In developing countries, surveys often have considerable problems accommodating self-employment and formal economic activities. Many households have multiple and continually changing sources of income, and home production is frequently diverse. In these contexts, it is generally impossible to get an accurate measure of income. For such reasons, some analysts developed methods to estimate household permanent income using information on ownership of selected assets or on the use of certain services that correlate with permanent income (Morris *et al.*, 2000).

Because of the abundance of household survey data on asset ownership and the numerous biases and measurement errors associated with reported income, a substantial literature has developed on asset-based measures of income. As in Howe *et al.* (2008), the simple case is to use an asset index based on the number of household assets (agricultural and non-agricultural) from a defined set of owned goods.

For instance, including assets (productive and non-productive), educational variables, information regarding employment status and other proxies in the resilience model, will guarantee that income-generating capacity is captured. Non-exhaustive examples are productive assets (livestock and land inputs), non-productive assets (house, car, and motorcycle as household wealth indicators), human capital, physical and financial capital, common and public goods, returns to activities and returns to savings. Income stability could also fit into this.

Following utility theory, household utility is considered to be a function of asset ownership (A_{ij}), taking the value of either zero or one depending on whether household i owns asset j, and consumption of other goods (M_i). In other words:

$$M_i + \sum_{j=1}^{J} p_j A_{ij} = Y_i \qquad (1)$$

Box 1. Dealing with income issues

where Y_i is household income and p_j the price of each asset in terms of the number of baskets of consumption goods needed to buy it. The basic assumption is one period model where income equals total value of expenditure during the period.

As an alternative to a simple sum of asset variables that are available in the data, it is possible to use statistical techniques to determine the weightings in the index. The two most common approaches for doing that are Principal Components Analysis (PCA) and factor analysis (Bartholomew *et al.*, 2002). These are essentially tools for summarizing variability among a set of variables. Filmer and Pritchett (1999) and Sahn and Stifel (2000) argued that FA is preferable to PCA because it does not force all of the components to explain the correlation structure between the assets accurately and completely.

Given what is stated above, RIMA-II methodology considers productive and non-productive assets to be the preferable proxies for income, meaning that income is not part of the resilience construction index. In order to make sure to include sufficient explicative variables, an income model is estimated in order to guarantee that the variables included are suitable proxies of income. Using the Uganda UNPS 2009-2010 dataset, Table 1 shows how the variables used in the construction of pillars explain income dynamics. They explain 67 percent of income variance, are very significant and show the expected signs.

Table 1. Output of the determinant of income

Variables	Log of income	Standard errors
Tropical Livestock Unit	0.00929	*1.408*
Participation index[8]	0.438***	*9.231*
Education of HH (Years)	0.0404***	*5.708*
Dependency ratio	-0.171***	*-8.817*
Agricultural asset	0.0918	*0.970*
Non-ag asset	0.256***	*11.510*
Transfer	0.00796	*0.365*
Distance to product market	-0.00120	*-1.440*
Constant	2.620***	*45.370*
Observations	2 240	
R-squared	0.67	

***: significative at 99%; **: significative at 95%; *: significative at 90%

[8] Participation index is created through the Rural Income Generating Activities (RIGA) methodology; this indicator reports the number of income generating activities (IGA) actively participated by the family. The index is at household level and ranges from 0 (no IGA) to 1 (the household participates to the entire set of IGA included in RIGA).

2.3.3 Social Safety Nets (SSN)

Access to transfers, whether cash or in-kind, represents a major source of poverty alleviation in many developing countries. Public and private transfers make up a substantial portion of poor households' annual income, providing important cash to generate additional income.

The SSN pillar includes both formal and informal transfers. While the former category is easily observed, informal social networks flowing through unrecorded channels are not easy to capture as they are not easily detected and quantified because they involve various forms of exchange that by definition take place outside formally institutionalized channels (Ligon, 2001; Mordoch, 1999).

Formal transfers are one of the principal areas of intervention intended to provide social protection and poverty alleviation for the poor through improved access to credit and subsidization of credit. The informal financial sector is also a key source of social protection, especially in areas with limited access to the formal financial sector. In many countries, such transfers are much larger than those handled by the formal sector. Freund and Spatafora (2005) showed that informal transfers amount to about 35 to 75 percent of formal ones in developing countries.

The extent to which households can refer to formal or informal channels depends mainly on the existence of healthy credit institutions, from the degree of a single individual's social connections and networks inside a community to the existence of public social protection intervention (Fafchamps *et al.*, 2007). The latter is a relatively new phenomenon in developing countries, especially in Africa, where it is provided on a pilot basis and only covers a fraction of the eligible population.

Informal transfers are important for households and individuals and act as an insurance mechanism. Households can borrow from friends and relatives in cash or in kind, but private remittances sometimes are not able to protect households from shocks. Public social safety nets, social protection and insurance programmes, even if of limited coverage in some developing countries, can help the poor to build up and protect their assets with the minimum of debt.

Formal and informal transfers complement each other, covering similar groups of people and meeting overlapping needs (Devereux and Getu, 2013).

Together with income, transfers are most likely the first response mechanism that is activated when a shock occurs. Access to different forms of transfer is an important indicator of social cohesion. The higher the level of cohesion within a community, the higher the probability that in the case of idiosyncratic economic problems the community will respond by providing resources to the person in difficulty.

Finally, there is growing agreement that social protection constitutes an efficient answer to poverty and food insecurity in developing countries (Mane *et al.*, 2015). SSN indicators, as in the case of in-kind or food received, could be complementary in the calculation of food security levels as well as in total consumption (Skoufias and Quisumbing, 2004).

Good proxies of formal transfers could be the amount of cash and in-kind assistance received, quality of assistance (for example, looking at the increasing or decreasing provision of services by public authorities, or number of people receiving incomes or wages from the state, dependency ratio etc.), frequency of assistance and number of people within the household receiving assistance, pensions (amount received, gender and position of the receiver within the household (Duflo, 2003)), remittances (Carletto *et al.*, 2004) and number of associations in which a household participates. Another possible proxy is the existence of microfinance institutions, which have been shown to affect household livelihoods positively (Asadul, 2012; Janzen and Carter, 2013).

Moreover, when it comes to informal transfers, it is important to consider the position of the head of household within the community, the ethnic provenance, age and familiar interconnection with other households or clans (La Ferrara, 2007; Duflo, 2003; Fafchamps *et al.*, 2007). The higher the social capital, the easier the access to informal transfers (Paldam, 2000).

2.3.4 Sensitivity (S)

S relates to exposure to risk as well as to persistence or resistance to shocks. Risk exposure refers to the extent to which a household livelihood is affected by a specific shock.[9] Smith and Wandel (2006) argued that sensitivity is not separable from exposure. If shocks come together (i.e. severe shocks are repeated over time) then coping is more difficult (Dercon, 2000). Expanding the definitions of persistence and resistance[10] (Batabyal, 2006), it is possible to define persistence as the amount of shock a system can absorb before becoming incapable of further reaction. A complementary definition is that for resistance, defined as how long it takes before the entire livelihood system of a household can be compromised by a shock.[11] This aspect of sensitivity builds on the definition in Adger (2006) "the extent to which a human or natural system can absorb impacts without suffering long-term harm or other significant change".

It is therefore important to assess the frequency and the intensity of shocks affecting a household over a given period of time. This can be done by including continuous variables in the estimation model, which report either the estimated or the actual loss suffered by the household. The most advanced surveys, as represented by the World Bank Living Standard Measurement Studies, report information regarding shocks. They ask people about the number of shocks reported on a monthly or even annual recall and the associated losses. The central question regards the extent to which the total combination of livelihood strategies can deteriorate as a result of a single or repeated shocks occurring over a given period of time.

In RIMA-II this pillar will be considered exogenous[12] and as such employed in regression analyses to evaluate the real impact of shocks on resilience capacity. Further details are given in Section 5.6.

2.3.5 Adaptive Capacity (AC)

Ecological and economic systems are non-linear and adaptive (Levin *et al.*, 1998) and therefore adaptive capacity of a household has to be taken into account. Adaptive capacity represents household ability to adapt to the changing environment in which it operates. This is a multidimensional concept, being determined by complex inter-relationships among a number of factors at different scales (Vincent, 2007). A household can become more adapted by improving its conditions in its own environment (Gallopin, 2006). One of the consequences of loss of adaptive capacity is the loss of opportunity, constraining options during periods of reorganization and renewal (Resilience Alliance, 2002).

The adaptive capacity in social systems is strictly connected to the existence of institutions and networks that represent learning and store knowledge and experience, creating flexibility in problem

[9] For instance, a pastoralist whose animals are facing a disease represents a different situation to a farmer or an entrepreneur facing a similar type of emergency.

[10] Batabyal (2006) elaborated the concepts of persistence and resistance from (Pimm, 1984). How long does it take the shocked system to manifest the full intensity of the crisis (persistence)? And how long does it take the unaffected part of the food system to become contaminated (resistance)?

[11] In other words, how long does it take a household to see its assets and coping capacities deteriorate? That is, being affected by one shock in five years is different from being affected by five shocks in five years.

[12] Meaning that sensitivity will not be part of the SEM.

solving and balancing power among interest groups (Berkes *et al.*, 2002). Having good adaptive capacity means being able to reconfigure without significant reduction in crucial functions.

Resilience is seen as the capacity not only to absorb disturbances, but also to reorganize while changes are taking place, so as to retain the same functions, structures and feedbacks (Alinovi *et al.*, 2008; Folke, 2006; Walker *et al.*, 2004). Therefore, the reorganizational capacity of a household is seen as fundamental in reacting to a shock and adapting to the new situation in order to get back to a given level of well-being. In ecological systems, this capacity includes mechanisms for regeneration, such as seed production and spatial recolonization, whereas in the social sciences it entails relying on intrinsic capacity of the household to find new solutions and generate new (and sustainable) livelihoods.

The capacity of adapting to perturbations and shocks is strictly connected with being able to learn from technological progress (Gallopin, 2006). Usually, the higher the literacy rate, the higher the adaptive capacity. Number of years of education has often been used as a proxy indicator of knowledge and skill, and exists as a key indicator in the United Nations Human Development Index (Abdulai and Eberlin, 2001). The least educated and lower skilled members of a society are likely to be the most vulnerable to climate hazards in terms of livelihoods and geographical location. It is important also to mention farmer knowledge in adopting new strategies to cope better with climatic shocks. Indigenous knowledge and experience of the environment is, in many cases, at least as useful as having a high level of literacy. Diversification of agricultural systems significantly reduces the vulnerability of production systems to greater climate variability and extreme events, thus protecting farmers and agricultural production. It could be interesting to include an indexes explaining the diversification of crop cultures (Brenda, 2011).

Regarding crop diversification, income diversification can also be considered an overarching strategy aimed at reducing risks and increasing options in the face of hazards (Turner II *et al.*, 2003). Under such circumstances the number of sources of income can be considered to be a proxy for adaptive capacity. If a household has many different income-generating activities, its capacity to withstand idiosyncratic shocks is higher.

It could be illuminating to include the percentage rural population as an indicator of dependence on natural resources sensitive to water stress and availability (Vincent, 2007), but this can be quite complex for what, by definition, is a measure that can vary at village level but not at household level.

Demographic structure of the household affects adaptive capacity (Vincent, 2007) by, for example, the lower the dependency ratio, the higher adaptive capacity. Furthermore, the presence of a chronically sick family member places extra burdens on a household and, thus, reduces its adaptive capacity. Therefore, illness indicators (adapted to the context) should be included in the RCI estimation.

3 UNIT OF ANALYSIS

This chapter describes the concept of household as the unit of the analysis. It goes through the literature starting from the food system concept, considering the household as the entry point and ending up with the food insecurity concept, considering the household the place where all the risk management decisions are taken.

The consequences of an entire sequence of actions cannot be predicted without understanding that the system can potentially be affected by them (Levin *et al.*, 1998). The natural candidate for resilience analysis in Less Developed Countries (LDC) is the Socio-Ecological System (SES) (Gallopin *et al.*, 2001). An SES includes social (human) and ecological (biophysical) subsystems in mutual interaction (Gallopin, 2006).

While a SES can be specified for any scale, from local community to higher administrative level, the initial focus of economic resilience analysis was to ensure that interventions could "support the resilience of endogenous food systems while addressing some of the main causal factors in the evolution of the crisis (Pingali *et al.*, 2005). Therefore, the main focus of this resilience approach is the food system.

Within the food system, the household can be seen as a sub-system that still fits into the system definition of Spedding (1988), "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 feedbacks".

When a shock occurs, households are the central decision-making units (consumption smoothing, asset selling, livelihood strategies choice, coping strategies adoption) and the node of interactions with institutions as well as with both formal and informal social networks (Alinovi *et al.*, 2010). As a consequence, the household is the entry-point for economic resilience analysis. A household is observed within the interaction framework where it lives, and therefore the relationship between the household and the broader food system it belongs to is important and contributes to household performance in terms of food security (Alinovi *et al.*, 2010).

For this exercise and with respect to FAO's mandate, resilience to food insecurity is estimated here. The household is regarded as the entry point for the food system, being the place where all the risk management related decisions are taken (Alinovi *et al.*, 2010).

4 DATA

This chapter describes the data included in the analysis. The econometric estimation is based on the Uganda National Panel Survey (UNPS 2009-2010, 2010-2011, 2011-2012), part of the World Bank Living Standard Measurement Study - Integrated Surveys on Agriculture (LSMS - ISA).

Household resilience can be measured using multidimensional surveys that focus on household behaviour. Considering the described resilience pillars, a resilience-oriented survey should include aspects of:

- income and income generating activities;
- access to basic services;
- access to infrastructure;
- productive and non-productive assets;
- formal and informal safety nets;
- social networks;
- shocks;
- food security indicators;
- institutional environment; and
- climate change.

Panel data are required for dynamic analysis and are defined as those data deriving from repeated surveys of the same population at different points in time. Cross-sectional data (i.e. survey interviewing one household on different aspects but in a single interview) do not suffice and do not satisfy the requirement for a dynamic analysis, in that they do not provide a trajectory of the studied variables. The dataset needs to be sampled in order to create a sufficient number of observations to be statistically representative of the study region.

In this exercise, the econometric estimations are based on the Uganda National Panel Survey (UNPS, 2009–2010, 2010–2011, 2011–2012), which is part of the World Bank Living Standard Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA). The sample is composed of approximately 3 200 households, including a randomly selected share of split-off households formed after the 2005-2006 UNHS (Uganda National Household Survey). The UNPS is representative at the national, urban/rural and main regional levels (Northern, Eastern, Western and Central regions). The initial sample was visited for two consecutive years (2009-2010 and 2010-2011). In the following years, part of the sample was replaced by new households extracted from the updated sample frames developed by the UBoS (Uganda Bureau of Statistics) from the 2012 Population and Housing Census.

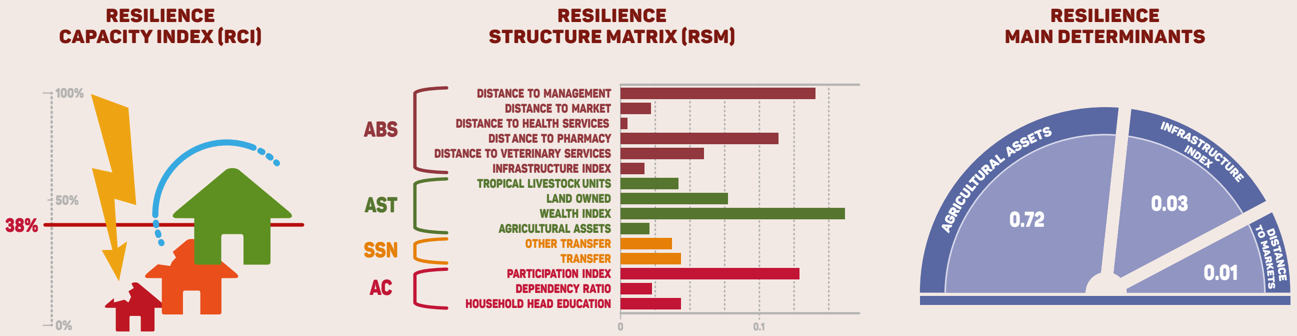
5 RIMA-II

This chapter provides a detailed description of the RIMA-II methodology. Given the dual nature of the resilience construction, both the direct and the indirect measure are deeply analysed: the first one through the MIMIC (Multiple Indicators Multiple Causes) model, the second one with its determinants.

RIMA-II comprised two parts, one direct (or descriptive) and one indirect (or inferential). The direct approach measures Resilience Capacity Index (RCI) and Resilience Structure Matrix (RSM). The indirect approach looks at the determinants of food security loss and recovery. The following paragraphs explain how RIMA-II is estimated.

The **Resilience Info Pack** follows, which includes the three sets of resilience measures cited above.

Figure 2. **Resilience Info Pack**



This info pack is composed of the three measures of RIMA-II. In the left part there is the RCI, which reports the extent of the resilient area. This can be adopted as a means for targeting and ranking. The RSM reports the correlates of the RCI and explains the situation for a specific point in time (Uganda 2011, in the example). This is a descriptive tool that presents the contribution of each variable to the RCI. Finally, the main resilience determinants are represented by the three most important variables that determine Ugandan household capacity for recovery. The Resilience Info Pack can be presented as a stand-alone informative package.

The following sections will describe how to generate these figures from the observed data.

5.1 DIRECT (OR DESCRIPTIVE) MEASURE

Resilience is an abstract capacity that is composed of various components (termed pillars). RIMA-II measures household resilience through the RCI and the RSM. The former is a measure of an agent's capacity (household resilience level) to avoid stresses and shocks having long lasting effects. Resilience structure explains how each pillar relates to resilience capacity (i.e. how much each pillar contributes to determination of resilience capacity) and how each observed variable relates to its pillar (i.e.: how much each variable contributes to determination of a resilience pillar). A direct measure of resilience provides a description of both resilience capacity and resilience structure. The resilience capacity is identified by the value of the RCI. Resilience structure is identified by the weightings that each pillar has in determining the resilience capacity and each variable has in determining the pillar.

RCI provides a useful baseline and policy analysis tool to inform, target and rank households and, therefore, it's a good base for funding and policy decisions for both government and civil society. As a ranking tool, RCI can both identify those household most at risk and to isolate the specific areas of resilience weakness that lie behind the increasing vulnerability. In this sense, the index can reflect issues of economic policy and growth.

RSM could encourage corrective policy actions that enable households to better cope with or withstand the consequences of a shock. However, latent variable models are hardly employed in inferential analysis: they are mostly employed as descriptive tool. RSM perfectly explains the combination of relevance of every variable in explaining resilience; however it omits the long-period effects and the non-linearity assumption; plus the predictions obtained through a latent variable model can be biased by measurement errors. The interpretation of the coefficients requires an integrated analysis of: values of observed variables; coefficients of pillars; coefficients of observed variables.

Low correlation between one variable and its pillar (or one pillar and the RCI) means that that variable is not contributing much to the pillar in that specific moment in time. However, for a full understanding of the reasons why this happens, one has to look at the other statistics (observed variables figures), comparing and crossing them with other studies and including long-term datasets (even better panel data).

5.1.1 Resilience Capacity Index (RCI) and Resilience Structure Matrix (RSM)

RIMA-II employs latent variables models to estimate resilience. Latent variable models assume that a) observed variables are manifestations of an underlying unobserved latent concept and b) other variables (correlates) construct and influence the latent factor(s), with a reciprocal effect. The chosen structure is highly relevant as there are several institutional, political and social arrangement factors that influence development and need to be taken into account. Not only do these factors influence the index performance but they are also influenced by it. A simple example is that if access to education is facilitated, i.e. knowledge capability is increased, development improves and this may in turn encourage people to demand free access to education for all (at least in a democratic setting), forcing the government to implement such a policy. This is because the process of development generates a virtuous cycle. Thus there is a feedback mechanism by which households (or individuals) promote their own factors. Unless this feedback mechanism is taken into account there is no possibility of having a complete picture of the evolving nature of the whole system (Krishnakumar, 2004).

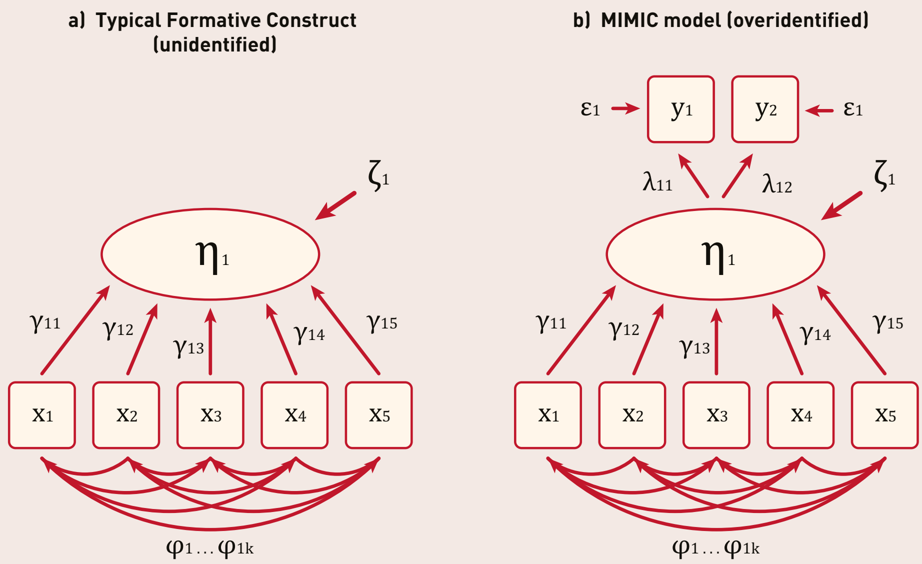
As in Kline (2012), five general conditions must occur before inferring the relationship between two variables (observable and latent):

1. the correlates are assumed to occur before the presumed effect (see Figure 1), termed temporal precedence;
2. there is an association between the latent and the observable variables;
3. their statistical association holds, controlling for other variables that can also affect the latent one;
4. the distribution of the latent variable is known because it matches the observed distributions; and
5. the direction of the correlates towards the latent variable is known; correlates influence the latent variable, and the correlates and the latent variable influence each other in a reciprocal manner.

The correlates are considered free to vary and to covary. Contrariwise, the indicator variables represented in the model do not.

A Multiple Indicator Multiple Causes (MIMIC) model[13] explains the relationship between observable variables and the unobservable variable by minimizing the distance between the sample covariance matrix and the covariance matrix predicted by the model. The observable variables are divided into correlates of the latent variable (they can be both endogenous and exogenous, as in Krishnakumar, 2004) and its indicators. The correlates are part of the structure of the model, while the indicators are measured (see Figure 3). The MIMIC model assumes that the variables are measured as deviations from their means and that the error term does not correlate with the pillars (correlates) (Buehn and Scnheider, 2008).

Figure 3. **MIMIC construct**



[13] MIMIC models belong to the SEM family. SEM (and, as a consequence, MIMIC models) have two measurement models: formative and reflective (Edward and Bagozzi, 2000). These models differ for the causal structure: a reflective model sees a latent variable as the cause of observed variables; the formative model sees the observed variables as the causes of a latent model.

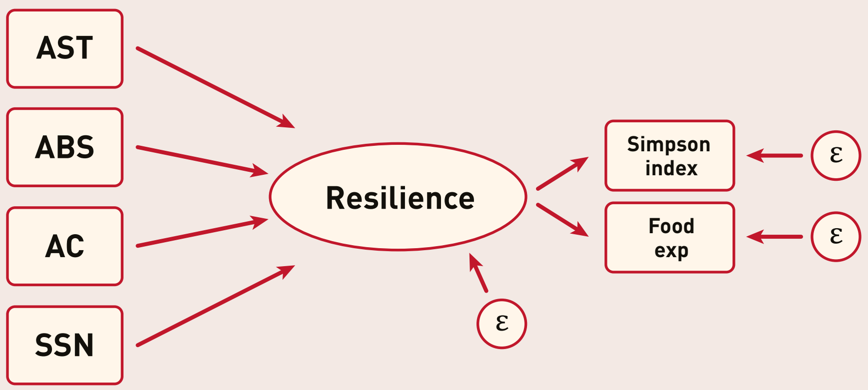
In RIMA-II, ABS, AST, SSN and AC are considered as observed endogenous variables that cause and can be in turn influenced by resilience. It is theoretically possible to include in the model a set of observed exogenous variables/causes (such as traditions, cultural elements, natural environment, social political and institutional aspects); they will be excluded in this model because of lack of data; this will remain however as a future opportunity.

Food security indicators, in this case monthly per capita food expenditure (Food exp), and dietary diversity (DD), are the achievements of resilience and are directly observables and measured.

This approach resolves the limitations mentioned in Section 2.1.[14]

The conceptual model forming the basis of the analysis of RCI (Resilience) is shown in the stylised path diagram of a MIMIC model in Figure 4.

Figure 4. **Resilience path diagram**



Following Buehn and Schneider (2008), the mathematical representation is:

$$y = \lambda\eta + \epsilon \qquad (1)$$

$$\eta = \gamma' x + \zeta \qquad (2)$$

where $(y_1, y_2, \ldots, y_n)$ are indicators of the latent variable η, γ is the coefficient of η and $(x_1, x_2, \ldots, x_k)$ are causes of η. In particular equation (1) says that y values are congeneric measures of η, meaning that they all measure the same construct.

In order to test the hypothesized relationship between the determinants and effects of resilience, the following (baseline) MIMIC model of resilience $(\eta,)$ has been implemented. The measurement model is specified by the Simpson index,[15] which is a measure of diet diversity, and the household per capita food expenditure (Food Exp), which is an indirect measure of food caloric intake:

[14] In particular, food security indicators are employed as indicators of resilience. Shocks have been removed by the estimation procedure and, therefore, their effect on resilience is analysed separately.

[15] Dietary Diversity score was calculated using three methods: Shannon and Simpson index and the typical category-based dietary diversity. Simpson index was adopted in this model because the MIMIC results fit better in terms of goodness of fitting and other tests (CFI, RMSEA, TLI and Chi-2).

$$\begin{bmatrix} Simpson\ index \\ Food\ Exp \end{bmatrix} = [\Lambda_1, \Lambda_2] \times [\eta] + [\varepsilon_2, \varepsilon_3] \tag{3}$$

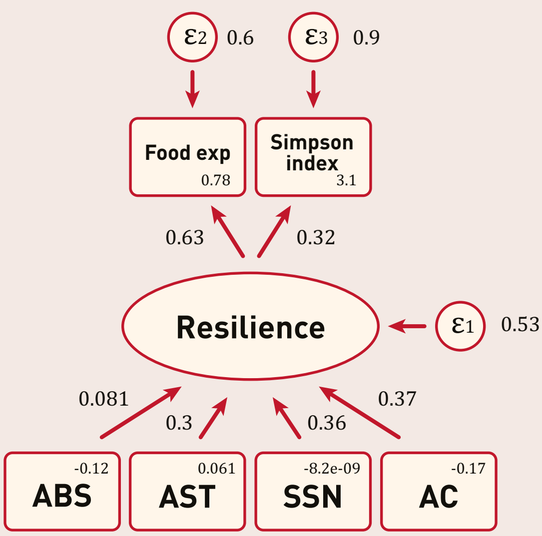
The basic causes of the structural model used in the modelling process of the MIMIC model are ABS, AST, SSN and AC, in other words:

$$[\eta] = [\beta_1, \beta_2] \times \begin{bmatrix} ABS \\ AST \\ SSN \\ AC \end{bmatrix} + [\varepsilon_1] \tag{4}$$

In the formative model, the hypothesis is that resilience (η) is influenced by the pillars (x_i). Formative indicators are assumed to be correlated and to be measured. In the reflective part, the model's reflective indicator errors (ε) are correlated and assumed to contain measurement errors. The MIMIC model permits simultaneous estimation of the measurement model and the incorporation of causal variables in the structural model for the latent variable Res, which is linearly determined (apart from random errors, ε_1) by formative indicators or pillars, and Res determines the observed reflective indicators (apart from random errors, ε_2, ε_3) (Lester 2008).[16]

The model represented in Figure 5 was specified using the Uganda UNPS panel dataset in a pooled version (for statistics of the pillars and related variables, see Annex IV):

Figure 5. **RIMA-II representation**



16 For reflective indicators, it is also necessary to ensure that indicators are measured on the same scale (Lester 2008). MIMIC model is applied for cross sectional data and panel data, the difference is in the way the model is constructed. For panel data it's better to run a pooled MIMIC in order to have a comparable latent variable across years.

The latent variable Res is jointly estimated by its causes and indicators. On the bottom of Figure 5 the structural model indicates the relationship between the determinants of resilience measured with error ε_1, the disturbance term of the structural estimation. In the upper part of the path diagram the arrows directed towards DDI score and per capita food expenditure indicate the measurement model.[17] Since the latent variable Res is inherently unobserved, there is no natural scale or unit of measurement. However, in order to represent Res, a reference unit must be defined.[18] Therefore, the coefficient (Λ_1 loading) of food expenditure is not estimated, but it is restricted to unity, meaning that one standard deviation increase in Res results in a single unit increase in the standard deviations of food expenditure. This defines the unit of measure for the other lambda (Λ_2) and for the variance of both food expenditures and dietary diversity. Given the model above:

$$Simpson\ index = \Lambda_1\ RES + \varepsilon_2 \qquad (5)$$

$$Food\ exp = \Lambda_2\ RES + \varepsilon_3 \qquad (6)$$

5.1.2 Interpretation

The MIMIC model is estimated using a Maximum Likelihood (ML) estimator. Many empirical applications showed that using all the information available leads to unbiased and efficient estimates, which is preferable to list-wise or case-wise deletion (Collins *et al.*, 2001). Therefore, the number of observations does not change across specifications shown in Table 2, which reports the estimates using the same dataset (i.e. Uganda rotating panel for the years 2009-2010, 2010-2011 and 2011-2012) using two different estimation techniques: ML method, and Generalized Method of Moments (GMM).[19]

The top panel shows the correlates of the model. Each variable has a potential effect on the latent variable Res, and the coefficient describes the influence of the variables on the latent one. The central panel shows the measurement model, which represents the link between the latent variable and its indicators, i.e. the latent unobservable variable is expressed in terms of observable variables, and coefficients here represent the magnitude of the expected change of the respective indicator for a unit change in the latent variable. The lower panel displays fit statistics.

The estimated coefficients are statistically highly significant at the 1 percent level and have the expected sign, meaning that better access to basic services, greater access to assets and greater adaptive capacity influence positively RCI, and promotes better adaptive capacity. The MIMIC model estimates that the independent variable SSN is not statistically significantly different from zero in the GMM estimation procedure. The role played by SSN in resilience analysis is often controversial; households receiving public transfers, and in general social assistance, are often those that register low resilience indices. As a result and further considering that this analysis is not looking at determinants of resilience growth, correlation between social safety nets and resilience can be negative.

[17] In a path diagram the circle indicates unobservable aspects of the model, whereas the squares indicate observable variables. Note that the pillars are not observable but are themselves latent variables.

[18] Automatically, from the statistical software employed.

[19] The two approaches are model-based methods for dealing with incomplete data analysis (Little, 1992).

Table 2. **MIMIC determinants and indicators**

Covariates	ML	Z-statistics	GMM	Z-statistics
ABS	0.495**	*4.74*	0.509**	*4.48*
AST	0.964**	*17.12*	0.979**	*11.62*
SSN	1.849**	*21.12*	1.849**	*18.46*
AC	0.834**	*20.04*	0.795**	*13.34*

Measurement model	ML	Z-statistics	GMM	Z-statistics
Food expenditure	1.000		1.000	
Simpson index	0.010	*16.73***	0.011	*14.65***

Statistics	ML	GMM
Observation	6387	6387
Chi-square	28.74	23.82
(*P-value*)	0	0
RMSEA	0.037	0.033
Probability RMSEA<0.05	0.958	0.987
CFI	0.985	0.965
TLI	0.956	0.896

***: significative at 99%; **: significative at 95%; *: significative at 90%

In order to estimate not only the relative size of the parameters but also their levels, it is necessary to fix a scale for the unobservable latent variable. A convenient way to determine the relative magnitude of the variables is to set the coefficient of one of the measurement model's indicator variables to non-zero[20] (Bollen, 1989). Here the coefficient of the variable food expenditure is fixed to one.

The response of the RCI is expressed in units of standard deviation, for a single standard deviation change in an explanatory correlate variable holding all other variables constant (Bollen, 1989). ABS, AST and AC have important effects on the size of the RCI. For instance, the effects of the main causal variables of the model indicate that a one standard deviation increase in AST, for example, leads to an increase in the magnitude of the RCI by 0.22 standard deviations (using ML).

Turning to the indicator variables, given the fixed positive coefficient of food expenditure, the standardized coefficient of the Simpson index indicates that an increase in RCI of one standard deviation increases it by 0.01. The results are robust over the two specifications.

The test of the robustness of the results to different methods is displayed at the bottom of Table 3. The results do not change qualitatively and are largely the same quantitatively. The RMSEA evaluates the fit of the model based on the deviance between the estimated and the real covariances. Brown and Cudeck (1993) assumed that RMSEA values smaller than 0.05 imply a good model fit, which corresponds to a probability close to unity.

[20] The choice of the anchor does not change estimation results.

The two fit indexes suggested by Bentler (1990) are the CFI and the TLI. They indicate a good model fit with values close to unity Hu and Bentler (1999). Finally, the model performs better than a multilevel MIMIC model, which estimates both the pillars (as latent variables from observed variables) and the RCI, in a one estimation (see Annex III).

5.1.3 Rescaling and other statistical properties of the index

A further elaboration of RIMA is the possibility of rescaling the RCI estimate. There is an extensive literature on the reasons for and the consequences of rescaling options in statistics MacCallum *et al.* (2002), although some concerns have been raised about the consequences of rescaling in regression analysis (Blalock, 1961; Bring, 1994; Greenland *et al.*, 1986; King, 1986). The rescaling option is important for a number or reasons, especially for understanding and interpreting regression results (Gelman, 2008; Seber and Lee, 2003).

RIMA-II adopts a min-max rescaling to serve three purposes: a) easier regression interpretation; Beta's coefficient interpretation is much easier if the dependent variable (resilience) ranges from 0 to 1 or 1 to 100, b) impact evaluation. When an impact evaluation is run against the RCI, it is possible to assess whether the index has or has not increased by x percent, and c) thresholds. Although this option needs to be explored further, it will become much easier to set thresholds that are common and cross-countries valid.

A min-max scaling is used to transform the RCI value into a standardized index, ranging between 0 and 1 (or possibly 0 and 100). The linear s-caling is based on:

$$x_i^* = (x - x_{min}) / (x_{max} - x_{min}) \tag{7}$$

A note of caution has to be raised. Although resilience analyses run with different datasets will give results that appear comparable (i.e. one may be tempted to compare the resilience capacity level between two different samples), comparisons are not valid. The estimation procedure only allows for comparisons when two RCIs are estimated jointly. Otherwise separate datasets cannot be compared.

5.1.4 Effects of shocks on Resilience Capacity Index

Resilience capacity can be substantially reduced by shocks. While there are aspects of this deterioration that cannot be measured without time series datasets,[21] the immediate effect of shocks on resilience capacity can easily be detected in RIMA-II. The relationship between shocks and resilience is non-linear. Also, the number, frequency and intensity of shocks significantly affect household coping capacity. None of these issues can be easily captured through data collection and analysis. RIMA-II treats shocks as exogenous and estimates their effects on both the outcome of interest and the resilience capacity.

It is important to distinguish between exogenous and endogenous shocks. Exogenous shocks, such as drought and price increases, are not influenced by the household or individual characteristics, but endogenous shocks are. For example, sickness is influenced by investments in health care or the household environment. This distinction is important when trying to address endogeneity concerns in estimation (Vaitla *et al.*, 2012).

[21] I.e. datasets that allow analysis if the behavioural choices have proven to be effective or not in the long period.

Hazards can be either natural or manmade (Vaitla *et al.*, 2012), and can include both classes, especially in the context of protracted crises (FAO and WFP, 2010). There are typically two types of resultant shock a household can face, idiosyncratic (micro) and covariate (meso and macro) (Holzmann and Jorgensen, 1999).

Idiosyncratic shocks are, typically, detected through self-reported events in household survey (such as LSMS). These data have many limitations. Self-reported shocks are prone to recall and reporting bias (Bourdillon and Boyden 2014); especially given the intensity of them (for instance LSMS studies reported one case from Niger where people didn't report drought as a shock, provided that they were constantly used at it; another example is in Makoka (2008) where poor households who were affected by a particular shock did not report it during a survey at they considered it normal) and by specific characteristics of a population which make them more or less likely to report a shock (Hoogeveen *et al.*, 2005).

Covariates shocks (including climatic, politics, social, exogenous factors) can be detected through secondary data; this may include Geographic Information Systems (GIS) data; observation; other dataset collected through community or qualitative data collection. Covariates shocks can be easily integrated in a (food security or resilience) analysis; a vector of shocks plus an interaction elements between shocks and other indicators can be included in the estimation model. This is the approach followed by RIMA-II.[22]

In the framework of food consumption analysis, shocks have been disaggregated in order to evaluate individual impacts on consumption. Following (Hoddinott and Quisumbing, 2001; Skoufias and Quisumbing, 2004) the model below includes a vector of dummies reporting whether or not a shock occurred in the household.

$$\Delta \ln c_{hv,t\text{-}(t\text{-}1)} = \sum_{v,t} \delta_{v,t} (D_{v,t}) + \sum_i \beta_i S(i)_{hv,t} + \gamma X_{hv,t} + \Delta\varepsilon_{hv,t} \tag{8}$$

Where $\Delta \ln c_{hv,t\text{-}(t\text{-}1)}$ denotes the change in log consumption or the growth rate in total consumption per capita of household h, in community v, between period t and $t\text{-}1$. $D_{v,t}$ denotes a set of binary variables identifying each community separately by survey round (and is aimed at controlling for the role of covariate shocks).[23] $X_{hv,t}$ is a vector of household characteristics. $S(i)_{hv,t}$ denotes shocks such as crop damage due to pests, illness and other (i.e. idiosyncratic).

Or its variance without covariate shocks:

$$\Delta \ln c_{hv,t\text{-}(t\text{-}1)} = \alpha_i + \beta_i \ln Y_{hv,t} + \delta X_{hv,t} + \Delta\, \varepsilon_{hv,t} \tag{9}$$

Where β_i provides an estimate of consumption variability inclusive of both idiosyncratic and aggregate shocks.[24]

Table 3 shows the effect of shocks on RCI. The signs are in line with expectations. Regression, with a robust standard error, takes into account the year effect (for shocks statistics see Annex IV).

[22] As long as data allow this. In fact in this note no GIS-datasets will be adopted, while further analysis on this topic are being currently developed both by RIMA and other approaches.

[23] Common to each household within the same community and survey round.

[24] To the extent that risk-sharing takes place and covariate risk has a significant role in explaining household consumption changes, then it is expected that $\tilde{\beta} > \beta$ with the difference $\gamma = \tilde{\beta} - \beta$ summarizing the role of covariate risk in the growth rate of consumption.

Table 3. **Effects of shocks on RCI**

Shocks	Resilience	Standard errors
Weather shocks	-0.772***	*0.121*
Wage shocks	-0.528***	*0.142*
Poor	-3.434***	*0.0822*
Conflict intensity index[25]	0.0954***	*0.00512*
Mean of rain (1983-2012)[26]	-0.00472***	*0.00127*
Standard deviation from mean of rain	0.0347***	*0.00618*
Cov of rain	-13.17***	*-3.030*
Year 2011	-1.018***	*0.131*
Year 2012	-1.000***	*0.135*
Constant	2.412***	*0.662*
Observations	6 387	
R-squared	0.2921	

***: significative at 99%; **: significative at 95%; *: significative at 90%

5.2 RESILIENCE IN A DYNAMIC CONTEXT

The main purpose of creating an RCI is to contribute to food security analysis. As a consequence, a validation process is needed to make sure that what has been measured is useful. In other words, one has to answer the following question: does RIMA really measure resilience to food insecurity? One way to look at the answer is to check if the RCI is able to predict (or is correlated with) future household food security attainments.

Ciani and Romano (2011) presented a seminal paper on this using the case of Nicaragua. The authors showed that the RCI, estimated through RIMA-I, is a good predictor of household food security. The latter is measured both by the change in food expenditure between two time periods and a dummy variable describing food poverty status at time $t+1$.

In more detailed form, the RCI estimated at time t, can be regressed on a food security outcome measured at time $t+1$. The assumption is that at time t the household characteristics contribute to food security as well as level of resilience. Between t and $t+1$, some shocks can befall the household. Consequently, household food security at $t+1$ is the result of the interaction of household characteristics, resilience capacity and shocks. Given consistent shocks and characteristics between two households, the one that is more resilient at time t is expected to perform better in terms of food security at time $t+1$ than the other. In other words, the resilience capacity at time t is expected to contribute positively to household food security at time $t+1$, *ceteris paribus*.

[25] Data come from Armed Conflict Location and Event Data Project, which provides detailed data on conflict episodes for African countries.

[26] The coefficient is calculated as the difference between the amount of rainfall registered during 2015 and the long-term average (1981-2010).

This test is not easily replicable if resilience is estimated through RIMA-II because the latter employs food security variables as indicators of the measurement model, as described in the previous section. In other words, if a food security outcome is used in the resilience estimation, it cannot be used as outcome variable in a dynamic analysis.

Two are the possible options:

- estimate the RCI through RIMA-II and perform the dynamic analysis by using, when available, additional (with respect to those used in RIMA-II) indicators of food security. Some examples can be Household Dietary Diversity Score (HDDS) and child Mid-Upper Arm Circumference (MUAC) (Upton *et al.*, 2015). This option is very demanding in terms of richness of survey variables; and
- use and indirect measurement of resilience. This approach (described in the next section) avoids the estimation of the RCI and allows the use of the food security indicators (food expenditures or food consumption scores) for performing a dynamic analysis.

5.3 INDIRECT (OR INFERENTIAL) MEASURE

The direct measure of resilience uses a series of observed variables to compute an RCI through complexity reduction techniques. This index can be then used to infer the outcome indicator of interest (e.g. the food consumption score). In doing this, the RCI is computed as a household characteristic that stands on its own, without reference, for instance, to household exposure to shocks.

This approach can be viewed as an intermediate step towards a truly dynamic resilience analysis. If an appropriate dataset is available (i.e. panel or pseudo-panel), regressions can be run directly with the resilience determinant variables as Right Hand Side (RHS) variables and the relevant outcome variable on the Left Hand Side (LHS). This can be termed the indirect measurement of resilience, corresponding to the so-called uninsured risk approach to the analysis of vulnerability (Hoddinott and Quisumbing, 2003). In this case, household resilience emerges indirectly, looking at whether the outcome variable of interest (LHS) has decreased or not.

Specifically, this approach uses the determinants of resilience (including decision variables useful for policy-making) to infer a given level of well-being (outcome). Different options can be explored to identify the appropriate indicators of well-being (or of recovery), consumption differential, speed of recovery (defined as the average time needed to bounce back to the previous level of well-being) and depth of loss (defined as how much well-being has been recovered within a certain time period).

5.3.1 Outcome of interest in resilience analysis

Any resilience measure has to be indexed to a specific well-being indicator. A resilience capacity measure can be indexed to food security, poverty or any other well-being concept that represents a development outcome of interest (RM-TWG, 2014).

Resilience capacity can be formalized as:

$$Res_h = f\,(P_1, P_2, \ldots, P_n) \tag{10}$$

where the resilience capacity of a household h depends on a number of pillars that ranges from 1 to n. It is possible to adopt (1) as a regressor of food security:

$$Food\ security_h = f\,(Res_h, x_1, \ldots, x_n, \varepsilon) \tag{11}$$

where the outcome (food security) depends on household resilience and on various other variables.

The specific indicator to be used depends on the objectives and the scale of the analysis.[27] If the entry point of the analysis is the household and the outcome of interest is well-being, then a suitable welfare status indicator is household food security at a different point in time or changes in food security between two points in time. There are many different indicators for food security (Carletto *et al.*, 2013). In this exercise, food expenditure, Food Consumption Score (FCS) (WFP, 2008), caloric intake (Simpson and Shannon indexes) and DDI are adopted as indicators of food security. Although there are some limitations to this indicator (Baumann *et al.*, 2013; Wiesmann *et al.*, 2009), it is interesting to test how much it has changed over time and, eventually, draw evidence on the main determinants of its loss.

5.3.2 Food security loss determinants

Given that a household who managed to recover the previous level of Simpson index after a shock, can be considered as a resilient household, resilience analysis is interested into isolating the determinants of the bouncing back process. Therefore, panel data are required in order to follow a two-step procedure: a) selecting those who suffered a loss in the Simpson index due to a shock and b) selecting those (out of the first sub-sample) who managed to regain their original level of the index. By following this procedure it will be possible isolate the characteristics of those who reported a loss in Simpson index in Uganda and explore what are the main determinants of the recovery.

Just to have an idea of the intensity food insecure households, Table 4 below reports the percentage of households below and above the food security threshold of 2 100 daily caloric intake.

Table 4. **Total households in poor food threshold**

Daily caloric intake	Uganda 2009-2010 (%)	Uganda 2010-2011 (%)	Uganda 2011-2012 (%)
> 2100	50.3	41.5	49.6
< 2100	49.8	58.5	50.4
Total	100.0	100.0	100.0

In order to estimate the determinants of food security loss, a sub-sample of the population is followed, in particular those who have been affected by one shock between year 1 (2010) and 2 (2011) and reported a lower score in the Simpson index in year 2 are isolated. Table 5 details this sub-sample.

More than 53 percent of people registered a loss in year 2 (2011).

A probit model is now run, which seeks to understand the main determinants of the loss (and, as a consequence, those of resilience) by estimating which variable contributed most to the major or minor loss of Simpson index.

Mathematically it looks like the following model:

$$Pr\ (Y_h = 1) = \Phi\ (x_h\ \beta') \tag{12}$$

[27] A thorough analysis about the choice of the dependent variable would be very useful, but it goes beyond the scope of this paper.

Table 5. **Total households registering a loss in year 2 (2011)**

	Frequencies	%	Cumulative (%)
Non loss	1 098	46.56	46.56
Loss	1 260	53.44	100
Total	2 358	100	

That is to say that the probability of suffering a loss (if Y=1 means that the household registered a loss in food security) depends on a combination of factor x which include the entire vector of variables adopted for the resilience analysis in the direct measure. The probit analysis estimates the vector of betas (see Table 6 for results).

Table 6. **Main determinants of loss**

Variables	Loss in Simpson	Standard errors
Infrastructure index	-0.00842	*0.0361*
Distance veterinary centre (inverse)	0.101	*0.0676*
Distance primary school (inverse)	0.0630	*0.135*
Distance health centre (inverse)	-0.0440	*0.0852*
Input selling market (inverse)	-0.106	*0.111*
Non-agricultural market (inverse)	0.151	*0.0936*
Pc agricultural assets	-0.382***	*0.115*
Pc wealth index	-0.294***	*0.0894*
Tropical Livestock Unit	0.0204	*0.0757*
Pc transfers	0.00301	*0.00405*
Pc other transfers	-0.00713	*0.00900*
Scholarship (1 = yes)	0.390***	*0.0561*
Participation index	0.226***	*0.0810*
Education	0.0272***	*0.00697*
Dependency ratio (inverse)	0.0965***	*0.0291*
Constant	-0.447***	*0.0588*
Observations	2 358	

***: significative at 99%; **: significative at 95%; *: significative at 90%

Larger access to productive assets and wealth index decrease the probability of experiencing a fall in food consumption. Quite surprisingly Participation index and having access to a scholarship reduce food security. An explanation may be that those who have access to a scholarship are typically the poorest and targeted households. Participation index has a counterintuitive effect on the probability of losing food security. This, however, seems to be correlated with the great effect of a wage shock on food security (see table 7). It is likely that the findings are influenced by a strong occurrence of wage shocks which directly affect explicitly those whom work on a more urban and diversified environment.

It is also interesting to look at which shock had great influence on the loss. Table 7 shows the effects of self-reported idiosyncratic shocks on the amount of loss in Simpson index, together with other demographic and income variables.

Mathematically this is represented by

$$Loss = f\,(\beta_1\, Res_h + \beta_2\, X_{h,t} + \beta_3\, Z_h + \varepsilon) \quad (13)$$

That is to say that the amount of loss depends on the vector of variables Res which characterize the resilience analysis; a vector of time-variant variables X; and a vector of time invariant variables Z plus the error term.

Table 7. **Effects of shock on food security loss**

Variables	L1110	Standard errors
Female household head	0.0130	*0.0108*
Household size	-0.00904***	*0.00198*
Conflict intensity	0.00238***	*0.000855*
Livestock loss	-0.00410	*0.00651*
Crop shocks	-0.0304	*0.0378*
No food to eat	0.0205*	*0.0124*
Other shocks	-0.0574*	*0.0343*
Weather shocks	-0.0253**	*0.0105*
Wage shocks	0.0255*	*0.0137*
Mean of rain (1983-2012)	-0.000146	*0.000106*
Standard deviation from mean of rain	0.000326	*0.000534*
Cov of rain	0.0130	*0.256*
Log of food expenditure	-0.0565***	*0.00657*
Non movers	-0.0925***	*0.0309*
Constant	0.417***	*0.0528*
Observations	1 260	
R-squared	0.10	

***: significative at 99%; **: significative at 95%; *: significative at 90%

Conflict intensity is the most relevant shock (both sign and statistical significance are correct). Household size reduces the amount of loss; this can be explained if one considers that a greater number of household member can contribute to diversify the risk and smooth a shock's effect. It is a bit more complicated understanding why weather and other shocks have a negative effect on the amount of loss. But this can be influenced by the frequency and intensity of shocks.

A detailed analysis of what has happened to those who reported a shock is presented in Annex I. However, the real focus of a resilience analysis is to understand what made the difference in enabling a household to bounce back to a previous level of well-being. In other words, resilience analysis is very much interested in understanding the dynamics of a positive trajectory of the outcome of interest.

Figure 6. **Simpson index trajectory**

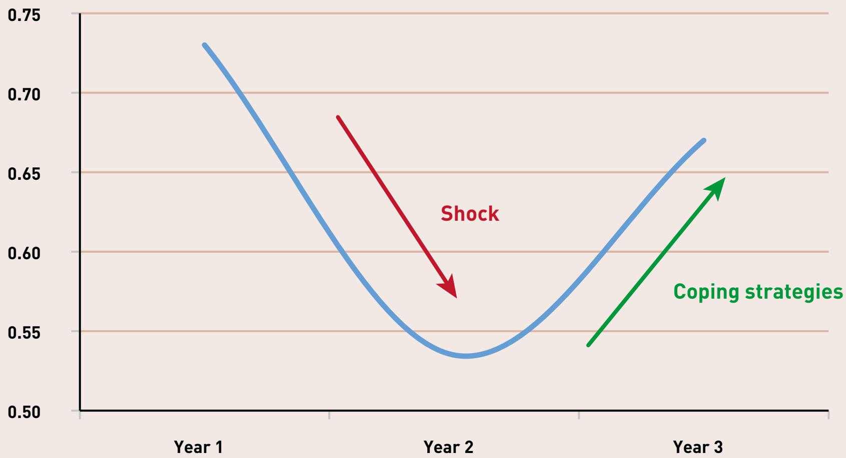


Figure 6 represents the trajectory followed by an the Simpson index level for those who received a shock between year 1 and year 2 and managed to recover (almost entirely) in year 3. Consequent analysis is focused on the sub-sample of the population that received a shock between year 1 and year 2. For instance, the research question is: what are the main drivers of a full food security recovery?

Table 8 reports a study on three possible scenarios for a loss in 2011: (1) are those who continued losing food security, (2) are those who managed to gain more food security and (3) are those who were able to bounce back to the same level of food security.

Unfortunately not many observations were reported because the Uganda dataset is not very large and the focus of this analysis narrows down the number of observations, but it is sufficient to draw inferences and conclusions from. An Ordinary Least Square (OLS) regression was run that included the vector of variables employed in the estimation of the RCI.

In the case of Uganda, having access to agricultural assets and being supported by transfers are the most relevant interventions to guarantee a prompt recovery from food security loss. Besides the statistical evidence, this finding is adequately supported by economic theory. A shock can destroy or compromise the means of living in rural communities. Typically, having access to agricultural assets can become an effective strategy for a) selling assets[28] and buying foods; and b) using assets to change livelihoods (switching, for instance, from pastoralism to farming) or to increase crops revenues.

There is an extensive literature supporting why transfers can be of fundamental importance during a crisis. Part of the literature has been cited in the section explaining why SSN is important and which indicators have been adopted. Transfers can represent a primary source of food. Transfers can be reinvested in inputs, can serve as guarantees for loans and can remove negative coping mechanisms. For these and other reasons, transfers are relevant for the capacity of a household to bounce back to a decent level of well-being.

[28] Time series data are needed in order to capture assets and consumption smoothing strategies adequately.

On the contrary, having a female-headed household can turn to have a negative effect on a household's capacity to bounce back from a shock.

The adoption of exogenous shocks related to climatic change and conflicts will help better understanding how resilience capacity and resilience determinants change over time and in response to a specific shock.

Table 8. **Simpson index trajectory outcome**

Variables	Loss in Simpson index	Standard errors	Gain in Simpson index	Standard errors	Same Simpson index	Standard errors
Female HH	0.157*	*0.0843*	-0.0526	*0.0821*	-0.178*	*0.106*
Household size	0.0247	*0.0151*	-0.0160	*0.0147*	-0.00965	*0.0180*
Infrastructure index	-0.0847	*0.0572*	0.0255	*0.0539*	0.0690	*0.0635*
Distance veterinary centre (inverse)	0.00195	*0.00177*	-0.00140	*0.00177*	-0.000818	*0.00231*
Distance primary school (inverse)	-0.00135	*0.00334*	0.000897	*0.00328*	0.000317	*0.00411*
Distance health centre (inverse)	-0.00204	*0.00172*	0.000969	*0.00168*	0.00186	*0.00209*
Input selling market (inverse)	0.00298**	*0.00128*	-0.00274**	*0.00130*	-0.000456	*0.00158*
Non-agricultural market (inverse)	-0.00347**	*0.00171*	0.00459***	*0.00170*	-0.00231	*0.00219*
Agricultural assets	-0.460	*0.290*	0.0214	*0.277*	0.718**	*0.348*
Wealth index	0.000581	*0.0392*	-0.0218	*0.0382*	0.0383	*0.0486*
Tropical Livestock Unit	-0.0481	*0.0571*	0.0615	*0.0537*	-0.0218	*0.0641*
Transfers	-0.00651	*0.00716*	-0.00135	*0.00608*	0.00803	*0.00656*
Other transfers	-0.0222	*0.0249*	-0.0125	*0.0188*	0.0310	*0.0199*
Scholarship (1 = yes)	0.0404	*0.115*	0.00455	*0.112*	-0.112	*0.142*
Participation index	-0.0135	*0.0118*	0.00587	*0.0113*	0.0143	*0.0139*
Education	-0.00400	*0.0427*	-0.00268	*0.0413*	0.0114	*0.0521*
Constant	-0.455***	*0.168*	0.0236	*0.163*	-1.002***	*0.202*
Observations	1 260		1 260		1 260	

***: significative at 99%; **: significative at 95%; *: significative at 90%

6 CONCLUSION

This chapter summarizes the main findings of the new approach in emphasizing the potentiality of it as a promising approach to understand the capacity of households to react to shocks. It also highlights the importance of the direct measure in ranking households and of the indirect measure in better exploring the different aspect of household food security.

Resilience represents a promising approach to understanding how households cope with shocks and stresses. This concept has been adopted in everyday programming, targeting and measurement activities. One of the most appealing features of the resilience approach is that it tries to identify how the combined effect of climate changes, economic forces and social conditions have increased the frequency and severity of risk exposure among vulnerable populations.

FAO has a long record of experience in measuring resilience, since its first attempts (Pingali *et al.*, 2005) with the RIMA approach and subsequently through the work of Alinovi *et al.* (2008). More recently, other scholars have proposed alternative approaches to measure resilience (Frankenberger *et al.*, 2012; Vaitla *et al.*, 2012).

RIMA has been validated over time as a good predictor of food security (Ciani and Romano, 2011; d'Errico *et al.*, 2016) and has been employed in many case studies. Other analysis indicated that RCI is largely correlated with food security and other poverty indicators.

Areas for improvement emerged as a result of consultations and discussions with experts and practitioners. They were consolidated and became a valid basis for the realization of a new version of the index. RIMA-II completely renews and substitutes for RIMA in estimation procedures and policy analysis. RIMA-II features a completely changed analytical framework and introduces two broad aspects of resilience measurement: direct and indirect.

Measuring resilience directly (i.e. with a single indicator proxy) is important for targeting and ranking purposes. It highlights the importance of resilience and the key contributors to resilience, acting as a descriptive tool. More generally it proxies the resilience capacity and describes the resilience structure of a household.

If the purpose of resilience analysis is to establish the main drivers of a recovery from a shock, regression analysis is needed rather than SEM and other latent variable models. Indirect measurement of resilience allows statistical inference on its main determinants. This ultimately translates into a greater capacity for policy indications.

Approaching resilience in such a way opens a wide range of opportunities to explore better and understand this aspect of food security. There are other areas that require attention, especially those related to long versus short-term coping strategies and their consequences. This aspect of resilience requires a large amount of data, which currently are not available. However, this may act also as an incentive for data collection, in order to provide all the stakeholders with the data required for the analysis.

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ANNEX 1

Taking Uganda as a sample country (years of reference are always 2009-2010, 2010-2011 and 2011-2012), in analysing better what happens to those households that registered a shock (in particular, an increase of shocks) in the second year (see Table A1).

Table A1. **Difference in shocks from 2010 to 2011**

Shocks from 2010 to 2011	Difference in frequency	Mean of total amount of the increase of shock	Min	Max
Animals lost	+47	1.91	1	9
Crop shocks	+12	1	1	1
Conflict shocks	+12	1	1	1
Death of a member	+20	1	1	1
Fire shocks	+7	1	1	1
Livestock disease	+14	1	1	1
No food	+56	1	1	1
Weather shocks	+85	1.04	1	2
Other shocks	+16	1	1	1

The second column shows the number of families that experienced an increase in different shocks. The third column shows the average of the increase. Third and fourth columns show the minimum and the maximum increases. The shock that affected more households seems to be the loss of animals, followed by weather shocks (see also the number of HH who experienced that increase, 85). Also not having food had an impact on households, translating into a decrease in the DDI employed in the analysis.

Households were also asked to rank from 1 to 3 a series of coping strategies adopted in order to recover from shocks. Table A2, A3 and A4 show the results.

Table A2. **Coping Strategy Index - Rank 1**

Coping strategies as first solution	Percentage
Relied on savings	14.56
Unconditional help provided by relatives/friends	11.33
Change in dietary pattern	8.89
More non-farm employment (wage or self)	4.56
More farm wage employment	1.56
Obtained credit	1.33
Change in cropping practices	1.11
Distress sales of animal shocks	0.78
Sold HH assets	0.67
Unconditional help by local government	0.56
Reduce health and education expenditure	0.56
Migration	0.33
Send children to live elsewhere	0.22

Table A3. **Coping Strategy Index - Rank 2**

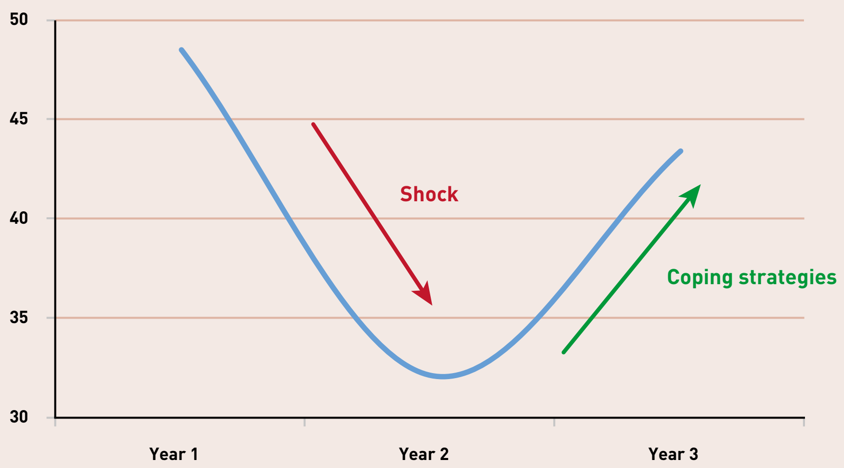
Coping strategies as first solution	Percentage
Change in dietary pattern	8.56
Relied on savings	8.44
Unconditional help provided by relatives/friends	6.44
More non-farm employment (wage or self)	6.11
More farm wage employment	2.67
Change in cropping practices	2.11
Obtained credit	1.89
Reduce health and education expenditure	1.33
Sold HH assets	0.89
Send children to live elsewhere	0.78
Unconditional help by local government	0.56
Distress sales of animal shocks	0.33
Rented out land/building	0.22
Migration	0.11
Sold land/building	0.11

Table A4. **Coping Strategy Index - Rank 3**

Coping strategies as first solution	Percentage
Change in dietary pattern	7.22
Unconditional help provided by relatives/friends	5.33
More non-farm employment (wage or self)	4.56
Relied on savings	4.00
Reduce health and education expenditure	2.33
More farm wage employment	2.11
Obtained credit	2.00
Send children to live elsewhere	1.33
Sold HH assets	1.11
Distress sales of animal shocks	1.00
Change in cropping practices	0.56
Migration	0.56
Unconditional help by local government	0.44
Rented out land/building	0.11

Figure 7 shows what happened to those households that experienced a shock in the second year, but recovered from it in the third year by applying specific coping strategies. FCS is adopted here instead of DDI or caloric intake.

Figure 7. **Food consumption score trajectory**



Regarding the following output, the relationship between the degree of loss and coping strategies is reversed. For example, using savings reduces the loss caused by a shock to an even extent than output saving, the best coping strategies adopted by households (see Table A5 for results).

Table A5. **Coping strategies**

Coping strategy	Log loss	Standard errors
Savings	-0.106	*0.0694*
Relative help	-0.0866	*0.0766*
Change in dietary pattern	-0.118	*0.0857*
Rely on self-employment	-0.140	*0.116*
Constant	2.646***	*0.0299*
Observations	900	
R-squared	0.0066	

***: significative at 99%; **: significative at 95%; *: significative at 90%

ANNEX 2

AGGREGATION PROCESS FOR RESILIENCE PILLARS

When dealing with a multidimensional measure, two aspects need to be considered: which pillars should be included in the estimation and how to aggregate them.

Well-being is intrinsically a multidimensional concept (Sen, 1985) and to measure it, an aggregation procedure has to be chosen. Similarly, resilience is a multidimensional concept and its estimation can benefit from the aggregation literature already existing for poverty measures.

An aggregation procedure creates a matrix of weight that represents the relation of each component to the resilience capacity.

Three aggregative approaches seem to be more frequently adopted:

1. non-aggregative strategies as in multidimensional poverty ordering and stochastic dominance (Esposito and Chiappero-Martinetti, 2008; Bourguignon and Chakravarty, 2003; Atkinsons, 2003; Duclos *et al.*, 2006);
2. multidimensional poverty index (aggregative) (Tsui, 2002; Bourguignon and Chakravarty, 1999; Bourguignon and Chakravarty, 2003; Alkire and Foster, 2008); and
3. multidimensional poverty analysis based on the use of multivariate statistical techniques (Krishnakumar, 2007; Krishnakumar and Nagar, 2008; Asselin and Vu, 2008).

RIMA-II employs the latter approach. The stochastic dominance approach can be very helpful in targeting or ranking for a specific purpose, i.e. classifying households or individuals into clusters or categories. However, this method does not show how different dimensions relate to each other and with the final construct. Alternatively, the aggregation process as in multidimensional poverty index estimation (Alkire and Foster, 2008) pre-assigns weights for each dimension (pillar). However, given that resilience is a context-specific concept, it is not possible to keep the weights constant over time and space (i.e. regions and countries). Therefore, weights have to be estimated every time a resilience analysis is run.

Following a multivariate statistical approach means dealing most of the time with latent variable models through observable (and measurable) precursors (Von Eye and Clogg, 1994).[29]

[29] This approach was originally used in psychometrics to estimate an unobservable concept such as intelligence.

Different techniques can be adopted: PCA, FA, SEM, MIMIC.

PCA is a data reduction technique that can be used to reduce the number of variables needed for a regression analysis (Cox, 2012), but is not used for any further analysis. PCA cannot be adopted to create a latent variable that is linearly correlated with the observable variables. PCA is computed with reference to no underlying structure caused by latent variables. Components are calculated using all of the variance of the observable variables, and all of that variance appears in the solution (Costello and Osborne, 2005). Also, PCA takes into account not only the variance of variables that can be attributed to the latent factor, but also that part of the variance that is uniquely attributable to the variable itself (the so-called uniqueness). Furthermore, very often the variables in resilience analysis are categorical or dummy variables: using PCA with dummy variables is not supported by adequate literature and the estimation of the variance/covariance matrix is complicated in the case of such variables (given the very low variance of dummy variables).

FA allows expressing a set of observed variables, used as a proxy for a latent variable (pillar), as a single variable, the component of interest. The variable reduction mechanism relies on finding cross-correlations between the observed variables, identifying number of (unobservable) factors reflected in correlations, and predicting the latent outcome (pillar) as a linear combination of underlying factors. If all the variables defining the pillar are closely correlated they may be represented well enough by a single factor. In the case that the variables cluster into a few groups of closely related variables, they are represented by more than one factor. The number of factors should be chosen so that at least 90 percent of total variability is explained.

SEM allow measurement of covariates between observed variables and correlations between the dimensions (Acock, 2013; Bollen *et al.*, 2007). One of the major differences between FA and SEM is that FA assumes that the residual errors (i.e. unique factors) are uncorrelated with each other and with the common (i.e. latent) variable. In food security, however, this assumption cannot be accepted, as the probability of intra-dimension correlation is high. Thus SEM seem to be better equipped in this case, allowing for correlation between residual errors (and a number of fitting tests). Although this method requires a greater computational effort than FA, it makes possible model calibration until a satisfactory level of goodness-of-fit is achieved.

When using these aggregation techniques, endogenity and multicollinearity issues need to be addressed. Multicollinearity exists when the assumption of no covariance between independent variables is violated:

$$Cov\ (X_1, X_2) \neq 0 \tag{14}$$

i.e. when there exists some covariance between two (or more) explanatory variables. The consequence of multicollinearity is that least squares estimates will have large standard errors and create biased estimation. One way to control for it is through preliminary correlation analysis or through the check of variance inference factors.

The second major issue is the violation of the assumption of no covariance between one of the variables of the model and the error term:

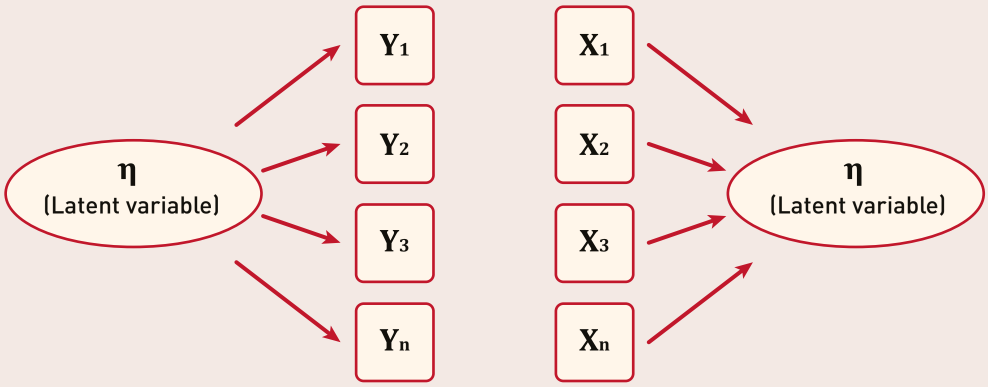
$$Cov\ (X_1, \epsilon_i) \neq 0 \tag{15}$$

In this case one of the regressor is correlated with the error term of the estimated model. Endogeneity is a relevant problem because it leads to inconsistent estimates. There are different ways to deal with endogeneity, such as looking for correlated missing regressors or adopting an instrumental variable approach.

MULTIPLE INDICATORS MULTIPLE CAUSES (MIMIC) MODEL

Classical SEM distinguish between two measurement models: reflective and formative (Edwards and Bagozzi, 2000). Figure 8 contrasts the different structures of the two models. In a reflective model (Figure 8, left panel), a latent variable is hypothesized as the common cause of items. The causal action flows from the latent variable to the indicators (arrays from latent variables to items). No specific indicator is expected to have a causal effect on the latent variable. Vice versa, a formative model (Figure 8, right panel) identifies a composite variable[30] that summarizes the common variation in a collection of indicators. In this case action flows from the independent variables (indicators) to the composite variable (arrays from items to latent variable). As noted in Bollen and Lennox (1991), these two models are conceptually different.

Figure 8. **Causal structures**



MIMIC model is a causal model with one underlying latent variable that has multiple indicators as well as multiple causes. In the linear MIMIC model, both the relationship between the latent variable and its causes and between the indicators and latent variable are linear in the parameters. The classical linear MIMIC model is specified as follows:

$$\begin{aligned} y_1 &= \beta_0 + \beta_1 \eta + \varepsilon_1 \\ y_2 &= \beta_0 + \beta_2 \eta + \varepsilon_2 \\ y_3 &= \beta_0 + \beta_3 \eta + \varepsilon_3 \\ &\ldots\ldots\ldots\ldots \\ y_n &= \beta_0 + \beta_n \eta + \varepsilon_n \end{aligned} \tag{16}$$

with

$$\eta = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \ldots + \alpha_k x_k + v \tag{17}$$

[30] A composite variable is considered to be composed of independent, correlated variables.

where:

η is the unobservable latent variable

$y_1, y_2, \ldots, y_n$ are the multiple indicators linearly related to x

$x_1, x_2, \ldots, x_k$ are the multiple causes linearly related to x

v is the Berkson error.[31]

Specifically, MIMIC models incorporate both formative and reflective components to measure latent constructs.

In the MIMIC model, the dependent variable (which is regressed on the formative indicators) is the shared variance of the reflected variables or constructs. The error term, is consequently the shared variance between the outcomes (i.e. the two or more reflective components) not accounted for by the formative indicators (Wilcox *et al.*, 2008).

Generally MIMIC is used to study the effects of covariates or background variables on the factors and outcome variables to understand measurement invariance and heterogeneity (Flora and Curran, 2004). Sometimes the complexities of factors that influence these coefficients make interpretations complex and non-intuitive. Firstly, they are not correlation coefficients, but standard deviations from the mean. For example, suppose there exists a network with a path connecting region A to region B. The meaning of the path coefficient theta (for example, equal to 0.81), means that if region A increases by one standard deviation from its mean, region B would be expected to increase its own standard deviation by 0.81 from its own mean, while holding all other relevant regional connections constant (Khalili-Damghani and Tavana, 2014).

[31] Berkson error is a random error in measurement, but unlike the classical error, Berkson error causes little or no bias in the measurement. In this case the model will have unbiased estimates, decreased variance, and robust parametric inference.

ANNEX 3

MULTILEVEL MIMIC ESTIMATION VERSUS TWO-STEP PROCEDURE

MIMIC model allows estimating the RCI by adopting a multilevel approaching estimating both (1) the pillars, as latent variables, from observed variables, and (2) the RCI, as latent variable, from the estimated pillars, in a unique estimation. This procedure would eliminate the estimation of the pillars through FA in a first step, as implemented by the RIMA-II approach. This annex compares the results of the two approaches.

Table A6 compares the results of the pillars' coefficients as well as the fit-statistics of the two approaches: in column (1) the two step approach (as presented in Table 2 in the text) and in column (2) the multilevel MIMIC.

As shown in Table A6, the coefficients of the pillars and food security indicators, estimated by the two approaches, are very close. Specifically the relative importance of pillars (ABS, AST, SSN, AC) is confirmed in both case. On the contrary, the two step RIMA-II approach, which employs FA for estimating the pillars, guaranties a better performance of the MIMIC estimation in terms of fit-statistics (as confirmed by the lower Chi2, higher Pr RMSEA, CFI and TLI). Furthermore, the multilevel MIMIC approach may create computational issues due to the number of employed variables. On the other hand, the two-step approach allows at including as many variables are relevant for estimating the multi-dimensional RCI in the different country-contexts.

Table A6. **Comparing results and fit-statistics**

Covariates	RIMA-II MIMIC	Z-statistics	Multilevel MIMIC	Z-statistics
ABS	0.495**	*4.74*	0.493**	*4.85*
AST	0.964**	*17.12*	1.027**	*17.57*
SSN	0.834**	*20.04*	0.519**	*10.36*
AC	1.849**	*21.12*	1.650**	*15.90*

Measurement model	RIMA-II MIMIC	Z-statistics	Multilevel MIMIC	Z-statistics
Food expenditure	1	*0*	1	*0*
Simpson index	0.010**	*16.73*	0.013**	*15.66*

Statistics	RIMA-II MIMIC	Multilevel MIMIC
Chi2	28.74	1750.03
P value	0.000	0.000
RMSEA	0.037	0.063
Pr RMSEA	0.958	0.000
CFI	0.985	0.972
TLI	0.956	0.961
Observations	6 387	6 387

***: significative at 99%; **: significative at 95%; *: significative at 90%

ANNEX 4

DESCRIPTIVE STATISTICS

Table A7. **Pillar factor loadings for ABS**

Factor loadings for ABS	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
Infrastructure index	0.12	-0.01	0.09	0.16	0.02	0.95
Inverse distance to veterinary	0.43	-0.02	0.27	-0.02	0.01	0.74
Inverse distance to primary school	0.74	0.24	0.00	-0.07	0.04	0.39
Inverse distance to health clinic	0.59	0.28	-0.06	0.06	-0.05	0.57
Inverse distance to input market	0.77	-0.25	0.04	-0.02	-0.05	0.34
Inverse distance to non-agricultural market	0.70	-0.20	-0.17	0.03	0.04	0.43

Table A8. **Pillar factor loadings for AST**

Factor loading for AST	Factor 1	Factor 2	Uniqueness
Per capita agricultural assets	0.36	0.00	0.87
Per capita wealth index	0.26	0.10	0.92
Per capita TLU	0.26	-0.10	0.92

Table A9. **Pillar factor loadings for SSN**

Factor loading for SSN	Factor 1	Factor 2	Uniqueness
Transfer	0.28	-0.03	0.92
Other transfer	0.08	0.07	0.99
Scholarship (dummy)	-0.29	-0.01	0.91

Table A10. **Pillar factor loadings for AC**

Factor loadings for AC	Factor 1	Factor 2	Factor 3	Uniqueness
HH average years of education	0.24	0.32	0.06	0.84
Dependency ratio (inverse)	0.15	0.20	-0.19	0.90
Participation index (income generating activities)	-0.47	0.19	0.11	0.74
Crop diversification index	0.55	-0.04	0.12	0.69
Inverse distance to input market	0.77	-0.25	0.04	0.34
Inverse distance to non-agricultural market	0.70	-0.20	-0.17	0.43

Table A11. **Pillars and related variables statistics**

Variables	Pooled	2010	2011	2012
Resilience Capacity Index	0.18	0.10	0.25	0.20
ABS	-0.01	0.02	0.13	-0.19
Infrastructure index	-0.10	-0.15	-0.01	-0.12
Distance to vet services (km)	22.36	29.77	17.42	19.88
Distance to primary school (km)	22.70	21.90	23.97	22.23
Distance from health services (km)	39.89	37.00	41.53	41.15
Distance to product market (km)	42.92	37.14	44.81	46.80
Distance to non ag. market (km)	34.50	34.52	35.47	33.50
ASS	0.11	0.16	0.08	0.09
Pc agricultural assets	-0.01	0.01	-0.03	-0.01
Pc wealth Index	-0.02	-0.03	0.00	-0.02
Pc Tropical Livestock Unit	0.20	0.22	0.18	0.19
SSN	0.00	-0.08	0.04	0.04
Transfers (US dollars)	1.56	1.48	1.75	1.45
Other transfers (US dollars)	0.39	0.43	0.50	0.25
Scholarship (1 = yes, 0 = no)	58.81%	60.69%	59.61%	56.13%
AC	-0.02	-0.03	-0.08	0.05
Participation index	0.27	0.29	0.27	0.26
HH average years of education	4.73	4.75	4.46	4.99
Dependency ratio	1.34	1.39	1.33	1.31
Crop diversification index	0.68	0.68	0.68	0.68
Food diversity indexes				
Food consumption score	42.70	40.81	42.76	44.52
Household Dietary Diversity Index	7.35	7.42	7.27	7.37
Simpson index	0.61	0.68	0.59	0.57
Shannon index	1.15	1.36	1.05	1.02
Pc daily consumption	2 501.62	2 501.62	2 272.06	2 731.19
Food expenditure (US dollars)	7.27	8.48	5.94	7.39
Total observations	6 387.00	2 129.00	2 129.00	2 129.00

Table A12. **Shock statistics**

Variables	Pooled	2010	2011	2012
Number of fire shocks	0.008	0.010	0.008	0.006
Length of shocks	1.827	2.737	1.465	1.279
Number of other shocks	0.028	0.039	0.023	0.022
Number of weather shocks	0.376	0.534	0.319	0.274
Number of wage shocks	0.112	0.149	0.122	0.065
Conflict intensity index	5.680	4.762	6.779	5.498
Mean of long period (1983-2012) rain	639.518	639.309	639.622	639.622
Standard deviation from mean of rain	145.900	145.851	145.924	145.924
Cov of rain	0.226	0.226	0.226	0.226

This document introduces RIMA-II, the technical evolution of the FAO Resilience Index Measurement and Analysis (RIMA) tool. RIMA was completely and deeply revised by the FAO Resilience Analysis and Policies (RAP) team; it was technically cleared by a restricted group of high-profile experts. RIMA-II will integrate the old version of RIMA with breakpoint and will guarantee extended analysis and new tools for measuring resilience.

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