FSIN
Food Security Information Network

Technical Series No. **2**

Resilience **M**easurement **T**echnical **W**orking **G**roup

A Common Analytical Model for Resilience Measurement

CAUSAL FRAMEWORK AND METHODOLOGICAL OPTIONS

Food and Agriculture Organization of the United Nations
IFPRI
WFP World Food Programme wfp.org
EUROPEAN UNION
USAID FROM THE AMERICAN PEOPLE

November 2014

FSIN
Food Security Information Network

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Acknowledgements

This paper was prepared jointly by Mark A. Constas (Cornell University), Timothy R. Frankenberger (TANGO International), John Hoddinott (IFPRI), Nancy Mock (Tulane University), Donato Romano (University of Florence), Chris Béné (Institute of Development Studies), and Dan Maxwell (Tufts University) under the overall leadership of Arif Husain, Chief Economist and Deputy Director, Policy, Programme and Innovation Division, World Food Programme (WFP) and Luca Russo, Senior Economist, Agriculture Development Economics (ESA) Division, the Food and Agriculture Organization of the United Nations (FAO). Detailed review was provided through a peer-review process in which Greg Collins (USAID), Jon Kurtz (Mercy Corps), and Rachel Scott (OECD) provided useful critiques on various aspects of the paper. Additional technical review was provided by the other members of the Food Security Information Network (FSIN) Resilience Measurement Technical Working Group: Tesfaye Beshah (IGAD), Gero Carletto (World Bank), Richard Choularton (WFP), Dramane Coulibaly (FAO), Marco D'Errico (FAO), Katie Downie (ILRI), Alessandra Garbero (IFAD), Ky Luu (Tulane University), Eugenie Reidy (UNICEF) and Nigussie Tefera (European Commission, Joint Research Centre).

The paper also benefited from detailed feedback and insights offered by John McHarris and Astrid Mathiassen (WFP). Thanks are due to Kostas Stamoulis, Director, Agricultural Economics Division (FAO) for his views on the paper and for useful discussions on the overall direction of the Resilience Measurement Technical Working Group. A special note of gratitude is owed to Alexis Hoskins (WFP, FSIN Secretariat) for the direction and guidance she has provided across all aspects of the Resilience Measurement Technical Working Group.

Véronique De Schutter (WFP) coordinated the editing, printing and publishing process, with support from Cecilia Signorini (WFP). Zoe Hallington provided much appreciated editorial assistance in the final review stages. Graphic design and layout services were provide by Energylink.

I. Background

The combined effects of climatic changes, economic forces and socio-political conditions have increased the frequency and severity of risk exposure among vulnerable populations. Recognizing the challenges created by more complex risk scenarios, the concept of resilience has captured the interest of varied groups of stakeholders concerned with how to reduce vulnerability and promote sustainable development. Resilience is viewed as valuable because it seen as providing a unified response to shocks resulting from catastrophic events and crises, and to the stressors associated with the ongoing exposure to risks that threaten well-being. The idea of resilience also holds particular appeal as a generalized ability to respond to an array of threats that have become more difficult to predict.

As interest in resilience has increased, so too has the need for a shared view of how to measure resilience. In recognition of this need, the Food Security Information Network established the Resilience Measurement Technical Working Group (RM-TWG).[1] The overarching goal of the RM-TWG is to provide guidance on how the analytical and procedural requirements of resilience measurement might be presented as a set of practices that are technically sound and conceptually well developed. To this end, the RM-TWG is focused on producing a series of papers, technical bulletins and consultation documents on different aspects of resilience measurement.

As the initial publication of the FSIN Resilience Measurement Technical Series, the first RM-TWG paper (Constas et al. 2014) described ten key design principles for resilience measurement.[2] The objectives of this first paper (referred to here as Paper No. 1) were to provide a clear definition of resilience and to describe the range of analytical demands associated with resilience measurement. It was important to begin with a clear definition because identifying key concepts is a precondition for sound measurement. Thus, Paper No. 1 offered the following definition of resilience:

> *"Resilience is defined as a capacity that ensures stressors and shocks do not have long-lasting adverse development consequences."*

Resilience capacity is therefore a concept with well-defined practical consequences. The actual contribution it might make to improving a given development outcome is best demonstrated through an empirically testable relationship that links resilience capacities to the outcome of interest. Paper No. 1 includes a basic formula in which resilience is identified as a predictor that can exert its influence in relation to other predictor variables. The function is expressed in the following simplified formula:[3]

Food security = f (vulnerability, resilience capacity, shocks)

1. The Resilience Measurement Working Group, co-sponsored by the European Union and USAID, is comprised of 20 individuals from government and non-government organizations. The full list of members is available at http://www.fsincop.net/topics/resilience-measurement/technical-working-group/en/
2. A detailed discussion of the design principles may be found at http://www.fsincop.net/topics/resilience-measurement/en/
3. Although food security is specified as the outcome of interest, the RM-TWG agreed that resilience measurement could also be applied to a wider class of development outcomes.

The inclusion of shocks and resilience capacity in the formula are two key features of resilience measurement: an optimal combination of resilience capacities can only be identified by measuring shocks. The formula is not meant to contain all the variables of interest; it was presented as a simplified expression that indicates the functional value of resilience capacity and sets the stage for more complete formulaic expressions upon which measurement work may be based.

As increased risk exposure is one of the main reasons for an interest in resilience, it is important to treat resilience as a capacity because of the effect that it may have on a food security or other development outcome in the face of shocks.[4] The inclusion of resilience capacity alongside vulnerability signifies that resilience is not merely the inverse of vulnerability. Rather resilience represents a particular set of measurable resources and capabilities that households, communities and other units (e.g., wider systems) may use to prepare for and respond to a shock or combination of shocks. Being vulnerable means having an increased probability of being exposed to risks, with such exposure presenting a threat to one's well-being. Resilience is a dynamic relationship that explains how a given set of capacities can reduce the vulnerability of a household (or other unit) and help it absorb, adapt and transform in the face of shocks and stressors. Thus, the function allows for the possibility that some populations can be both vulnerable <u>and</u> resilient. Much has been written about the relationship between vulnerability and resilience (see Adger 2006; Miller et al. 2010) and the issue of how best to represent the relationship as a function is still under debate. Understanding the exact nature of this relationship will ultimately be settled as an empirical matter by examining the results from studies that report on the interaction between vulnerability and resilience as predictors of food security and as predictors of other development outcomes.

Building on the principles and extending the definition of resilience offered in Paper No. 1, this second paper in the FSIN Resilience Measurement Technical Series is based on the premise that resilience can emerge as a topic of common interest only if a reasonable degree of consensus can be reached on how resilience might be measured. This is because measurement comprises the set of practices that allow one to translate concepts into technical practices that produce data. To help promote such consensus, this paper proposes a *common analytical model* within which the tasks of constructing resilience measurement may be specified and developed. At an operational level, the goal is to provide a resilience-focused analytical model to answer questions about what data should be collected, at what points in time, using what tools, at what levels and subject to what types of analysis.

The paper is organized into four main sections. As a preface to the common analytical model, section two describes the general purposes served by analytical models and highlights elements of selected analytical models of resilience measurement that have been applied to development. Section three describes the structural arrangement of the components that constitute the common analytical model. Section four describes each of the components and provides guidance on the methodological and analytical features of resilience measurement. The paper closes with a few comments that describe the utility of a common analytical model and highlight the kind of work that is needed to further advance resilience measurement.

4. Using a latent variables modelling approach to measure resilience, some of the foundational work on resilience (see Alinovi et al. 2009, 2010; FAO, 2014) treated resilience as both an unobserved outcome and as a predictor variable. Building on the FAO model, Ciani and Romano (2013) provided a focused analysis of how resilience can be used as a predictor of food security in the face of shocks. Recent work on the Resilience Index Measurement and Analysis model, the next generation of the FAO model, allows resilience to be treated as either a predictor or an outcome.

II. Preface to the Common Analytical Model

The data and insights generated by measurement can provide a basis for policy development, intervention and programme evaluation, and project implementation. Using measurement data as a foundation for action is best justified when the logic of measurement is well expressed. To this end, the common analytical model is meant to promote the articulation of the logic of resilience measurement.

To order to start describing the logic of resilience measurement, this section is structured around three objectives. First, it seeks to clarify the purpose of an analytical model compared with that of a conceptual model. Second, the modelling approaches used in a selected number of studies are briefly examined to identify some of the core components of the common analytical model for resilience. The reference to existing models of resilience acknowledges that significant work has been done on measuring resilience and that this provides a useful starting point for constructing a common analytical model for resilience measurement. Recognizing the importance of context, this section closes by describing the aspiration to propose a common analytical model that is both broadly applicable and sensitive to local conditions.

Conceptual models, analytical models and the utility of a common analytical model

Models are used in many fields to provide simplified expressions or illustrations of complex, often abstract, phenomena. Such expressions are useful because they focus attention on the most critical elements of a problem, programme or set of conditions. Models also suggest how those elements might be connected, theoretically or practically, thereby providing a more coherent account of some complex reality. Conceptual models and analytical models are often used interchangeably in problem modelling and programme development. It is therefore important to distinguish between these two types of model before explaining the purpose of an analytical model for measurement.

A conceptual model could take the form of a theory of change associated with an intervention, or a logic model used to organize an evaluation. It considers a set of relationships that are viewed as determining a particular outcome (e.g., food security, stunting or poverty). This type of model usually presents a graphic depiction of the relationship; it typically displays a chronological sequence and/or functional dependencies among the key elements that constitute the relationship. In this way, conceptual frameworks offer detailed nominal and relational information: objects of interest are named, cause and effect relations are suggested, and contextual factors are noted. However, from a measurement perspective, conceptual models do not show how to move from this graphic representation to the technical practices and analytical procedures that are central to measurement. While data elements and causal relations may be implied, conceptual frameworks do not usually specify what data will be collected, how they will be collected, and how they will be analysed. While conceptual frameworks attempt to capture the concepts and constructs that should be measured, analytical frameworks go farther by providing more specific guidance on how to measure and estimate actual indicators related to a given construct – in this case, resilience.

Analytical models for measurement are similar to conceptual models in that they may include a graphic depiction which shows how a collection of concepts, constructs or variables can form a network of causal and associational relationships. Analytical models for measurement have several distinctive characteristics. First, they provide guidance on the set of indicators required to gain empirical access to concepts, constructs and variables. Second, analytical models include formalized directions for drawing inferences from data. They can therefore offer a framework to help develop an empirically testable set of propositions. Third, analytical models of measurement contain technical criteria that allow one to judge the integrity of the data associated with a given set of indicators. Analytical models for measurement must reflect concerns about the accuracy (validity) and consistency (reliability) of data. Fourth, analytical models for measurement include detailed guidance on how to construct and use well-identified estimation models and data analysis procedures. The specification of estimation models and the description of analyses are fundamental to drawing conclusions from measurement data.

To summarize, the end result of an analytical model for measurement is a causal model that leads to a set of indicators, supported by technical criteria. An analytical model should also describe estimation procedures and other approaches used to draw inferences from data. Finally, analytical models contain procedural information that provides guidance on what actions need to be taken to generate and analyse data.

The importance of context in resilience measurement

One of the challenges of developing generalizable guidelines for action, such as a common analytical model for measurement, is that context matters. If resilience programming and measurement activities are strongly dependent on context, how can a common analytical model be sensibly specified? Here, it might be useful to distinguish between the ambition to generate common measures or indicators of resilience, and the ambition to generate a common analytical model that articulates a generalizable framework upon which measures may be developed. While the present paper will suggest categories of indicators that might be included in the measurement of resilience capacities, the specific indicators to be used will depend on context and the needs of those who work directly in the field.

The failure to identify indicators that reflect the complexities of local settings and satisfy the technical demands of measurement is often rooted in an incomplete consideration of context. For those concerned with the technical demands of measurement, the imprecise description of context will likely result in an underspecified problem. Underspecified problems typically generate poor models with weak prediction. For those whose work is more directly connected to the programmes and the settings in which they are implemented, insensitivity to context can produce measurement results that are irrelevant. In recognizing the importance of context, this common analytical model seeks to describe a measurement logic that can be applied across a range of settings, populations and interventions associated with resilience.

5. The ideas of specification and identification are of longstanding interest to the field of empirical economics. Though the work on resilience extends beyond the field of economics, the concepts of specification and identification will be used in the present paper to formalize various aspects of the common analytical model.

Building on knowledge gained from existing models of resilience measurement

Various conceptual models for resilience measurement have been developed by researchers, non-governmental organizations, and national and international agencies. Of the growing number of models now in circulation, a limited number are supported by one or more empirical studies (see Alinovi et al. 2009 and 2010; Ciani and Romano 2013 Maxwell et al. 2013; Smith et al. 2014).[6] An analysis of indicators and modelling procedures used in the four cited approaches reveals a good deal of consistency on the substantive elements (what needs to be measured) and the methodological features (the type of data collection tools) needed for resilience measurement. In the interest of brevity, seven key characteristics of resilience measurement found in one or more of the four selected models are highlighted:

1. **Types of shocks** – Data on shocks may include widely experienced shocks (covariate shocks), local or individualized shocks (idiosyncratic shocks), and low-intensity stressors that can have a cumulative negative effect on development. Specific types of shock that contribute to resilience measurement include, for example, the effects of climate change, distinct weather events, conflict shocks, economic shocks, geological shocks, pests and disease.

2. **Objective and subjective measures** – Data on shocks may include objective measures that record basic data on shocks and stressors (i.e., intensity, scope, frequency) and subjective measures (i.e., the perceived effect of shocks and stressors).

3. **Resilience capacities** – Resilience capacity is necessarily multidimensional. It must encompass a range of indicators including economic (assets, markets, supply chains), social (social capital, social networks), technological (agricultural practices), environmental (resources, natural resource management practices), infrastructure-related (roads), safety (conflict mitigation practices) and institutional (government) resources and capabilities.

4. **Resilience dynamics** – Resilience capacity is time and event dependent. The effect that resilience capacities have on well-being in the face of shocks can be found by measuring well-being before and after shocks.

5. **Grouping indicators** – Factors such as the location of a target population or the type of livelihood group affect both the probability of being exposed to a shock and/or stressor, and the capacities a target population has available to absorb, adapt, or transform in the face of shocks and/or stressors. The four studies collected locational and other data in order to analyse sub-groups.

6. Brief summaries of the models used in each of the studies cited are provided in the Annex.

6. **Environmental context** – The environmental conditions in which people live enable or limit their risk exposure and the opportunity to absorb, adapt and transform in the face of shocks. Thus a range of environmental factors are considered, such as climate and climate change, the state and management of natural resources, agro-ecological zones and changes in the risk landscape associated with the environment and ecological systems.

7. **Types of data** – Resilience measures may include a selection of quantitative and qualitative data, thereby generating the data needed to examine relationships, to construct and test prediction models to assess impact, and to describe local contexts in detail.

Although this is not a comprehensive review of the available resilience measures, the analysis of the four cited approaches helps validate recommendations from Paper No. 1 and provides details on measurement that inform the development of the common analytical model for resilience measurement proposed in section three of this paper.

III. Resilience Measurement Common Analytical Model

A common analytical model for resilience measurement provides a logical structure within which the process of developing measures might be organized. The aim is to present a model that can be adapted to meet the needs of specific measurement situations while ensuring some degree of standardization across all measurement exercises.

To promote a shared perspective on resilience measurement, the common analytical model presented here comprises six components, each of which addresses a practical measurement question:

- **Resilience construct assumptions** – What are the basic assumptions about the nature of resilience capacity that will influence the selection of indicators used to construct measures?

- **Resilience causal framework** – How is resilience capacity positioned in a dynamic relationship that explains well-being in the face of shocks? What types of indicators need to be measured, at what points in time, at what scale and using which methods in order to measure the effect of resilience?

- **Resilience indicators and data structure** – What specific indicators are needed to measure resilience? What special characteristics of those indicators might help model resilience dynamics?

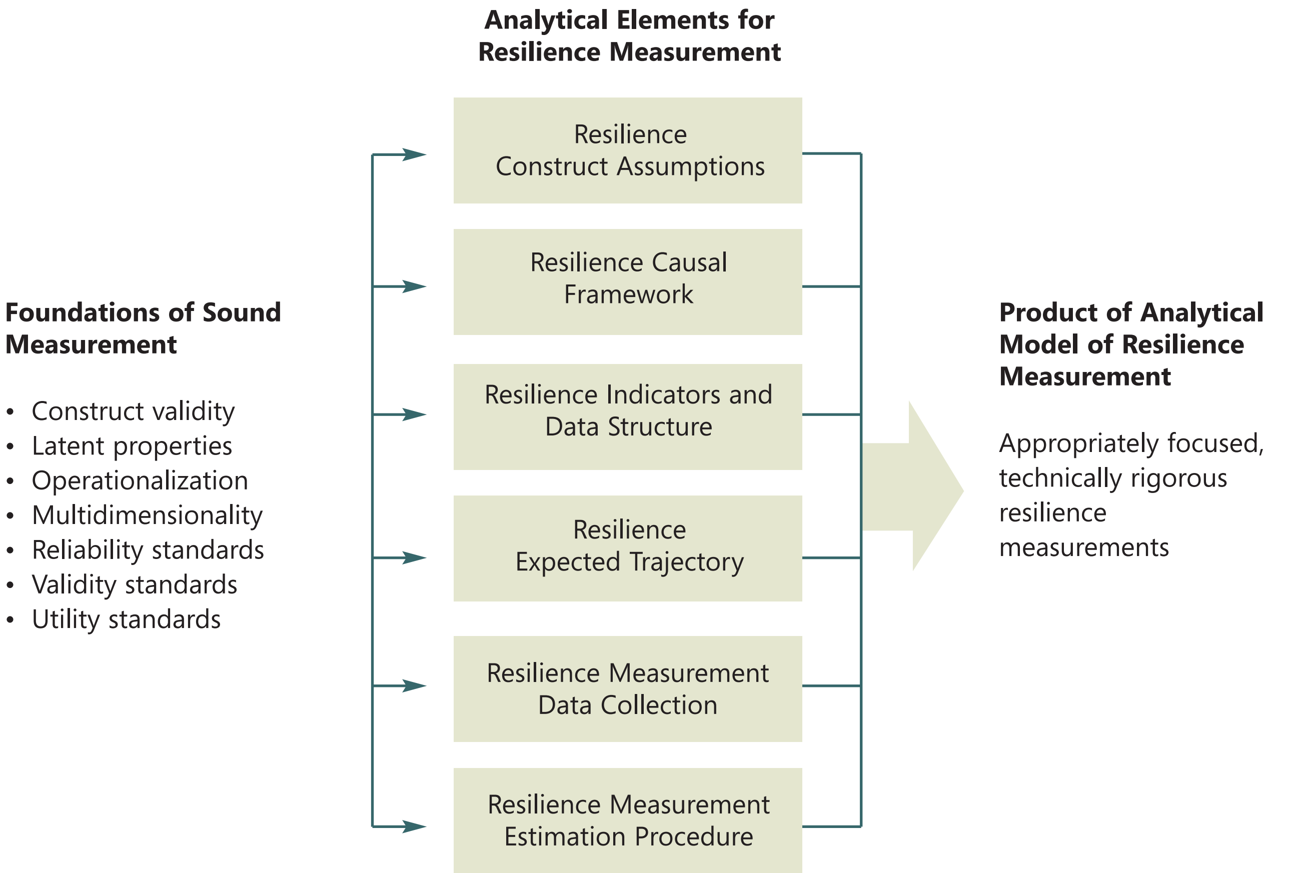
- **Resilience expected trajectory** – What is the expected rate of change? What factors affect the rate of change of development outcomes over time, in the face of shocks and stressors, and in relation to interventions and contexts?

- **Resilience measurement data collection** – What types of data collection tools and perspectives are needed to obtain accurate data on resilience?

- **Resilience measurement estimation procedures** – How might data be analysed to draw inferences about the effect resilience capacities have on development outcomes in the face of shocks and stressors?

The common analytical model is based on accepted foundations of measurement practice derived from classical (e.g., Crocker and Algina 1986; Cronbach and Meehl 1955; Nunnally and Bernstein 1994) and contemporary (e.g., Preacher et al. 2013) theories of measurement. Figure 1 shows the analytical elements and their foundational measurement practices, as well as the six components that constitute the common analytical model for resilience measurement.

Figure 1. Components of the common analytical model for resilience measurement



Building on the basic definition of resilience provided in Paper No. 1, the portion of the model labelled *Resilience Construct Assumptions* gives a more detailed definition of resilience as the object of measurement. The *Resilience Causal Framework* and the *Resilience Indicators and Data Structure* components are the core of the analytical model. The former describes the causal pathways, while the latter addresses the substantive elements of resilience measurement. Highlighting the importance of measuring change over time, the *Resilience Expected Trajectory* component provides insights into the path-dependent nature of resilience. The *Resilience Measurement Data Collection* component describes how multiple data collection approaches are needed for resilience measurement, with special attention given to collecting contextually sensitive data at multiple scales. Finally, the *Resilience Measurement Estimation Procedure* component explores different approaches to identify how resilience-related variables can be organized to predict well-being in the face of shocks.

These six analytical components are explored in detail below. The discussion of each starts with a practical measurement question highlighting the importance of that component in the process of developing resilience measures. While each component is important, the *Resilience Causal Framework* (component two) is perhaps most central to advancing a common analytical model for resilience. This is because causal frameworks have implications for the theories of change that guide programming. They also specify a causal relationship that will inform the contents and structure of an estimation model.

Component 1. Resilience Measurement Construct: Elaborating upon the basic definition

- *Practical measurement question:* What are the basic assumptions about the nature of resilience capacity that will influence the selection of indicators used to construct measures?

All measurement requires a clear definition of the construct to be measured. Definitions then need to be developed in order to specify indicators. In the case of resilience, Paper No. 1 defined it as *"a capacity that ensures stressors and shocks do not have long-lasting adverse development consequences."*

A key part of the definition in need of elaboration concerns the temporal features of resilience. The resilience construct and associated measurement can be located at two different points in time. First, resilience can be measured to produce a set of ex-ante indicators that are hypothesized as representing characteristics that predict the future well-being of a reference group, such as a household or community, in the face of shocks. Ex-post indicators are also needed to examine how one or more sets of well-being indicators change over time for a target group. Well-being may be measured in terms of several types of indicators (e.g., food security, poverty, physical health, safety) or through a combination of indicators. While both ex-ante and ex-post indicators are needed to model resilience, it is important to keep resilience firmly positioned as a capacity. The general assumption here is that investments and development programmes can help to support or build resilience capacity.

While it is true that certain well-being outcomes that change over time in the face of shocks and stressors may provide evidence of the effect of resilience capacities, this does not mean that these indicators (e.g., food security or poverty) are the equivalent of resilience indicators. The focus of the resilience construct advanced here is resilience capacities, whose influences can be measured against a given outcome such as food security or poverty.

There are four additional features of resilience as an ex-ante capacity:

1. Resilience capacity is a *positive influence*: it is meant to improve well-being outcomes in the face of shocks and stressors. While there are negative factors that are important for predicting well-being outcomes, these factors should not be counted as part of the resilience capacity construct. To the contrary, negative factors are – by definition – incapacities. As such, they may be vital for modelling but are distinct from resilience capacity.

2. Resilience capacity is defined as a *multi-dimensional* human-centric construct. It is therefore seen as residing in human attributes and in the processes and structures created by humans. Structures and processes include institutions, systems of governance, policies and programmes.

3. Resilience capacity depends on the *characteristics of the environments* on which the well-being of shock-prone populations depend. Environments include the set of ecological resources or services and the agro-ecological conditions that are important for food security, livelihoods and other development outcomes. Environmental conditions also influence the severity of a shock. For example, the impacts of flooding and droughts are magnified by degraded lands that cause higher run-off rates and the depletion of essential soil nutrients.

4. Consistent with perspectives developed in the field of ecology (Folke et al. 2002) and applied to development studies (Béné et al. 2012; Frankenberger et al. 2014), the resilience construct is seen as representing *three types of capacities* in response to shocks and stressors: i) the capacity to absorb shocks and stressors, ii) the capacity to adapt to shocks and stressors, and iii) the capacity to transform in the face of shocks and stressors. It may therefore be useful to know how different capacities (e.g., human capital) contribute to the ability to absorb, adapt or transform in the face of shocks.

Combining these four features with the key characteristics of analytic models summarized earlier produces a set of basic claims that bring further definition to the resilience construct provided in Paper No. 1. To elaborate on the definition originally provided, the resilience construct can be viewed as:

- An *ex-ante capacity* that serves a *predictive function*. The effect of resilience capacity may be observed ex post in connection with selected indicators of food security and well-being;
- Exerting a *positive effect* on food security and well-being in the face of shocks and stressors;
- Supporting different *functional outcomes*, including the ability to absorb, adapt and transform in the face of shocks;
- A capacity that resides in households and in the larger aggregates (e.g., communities, institutions) that support households;
- Something to be observed at a given point in time and over extended periods because the effects of resilience capacity are *path-dependent and time-sensitive*;
- A *multi-dimensional construct* comprised of human, social, financial, physical and natural resources or capitals;
- A *multi-level construct* where the indicators needed to model resilience may be drawn from households, communities or higher levels, depending on the nature of the intervention and the associated theory of change/causal model; and
- Fundamentally connected to an interdependent set of ecological resources and agro-ecological conditions on which the capacity to respond to shocks and stressors strongly depends.

As elaborations on the basic definition, these eight aspects of the construct are consistent with the resilience measurement principles described in Paper No. 1, and they help focus the set of indicators that might be used to measure resilience. This presentation of resilience as a construct is reflected at various points in the description of the elements of the common analytical model that follows.

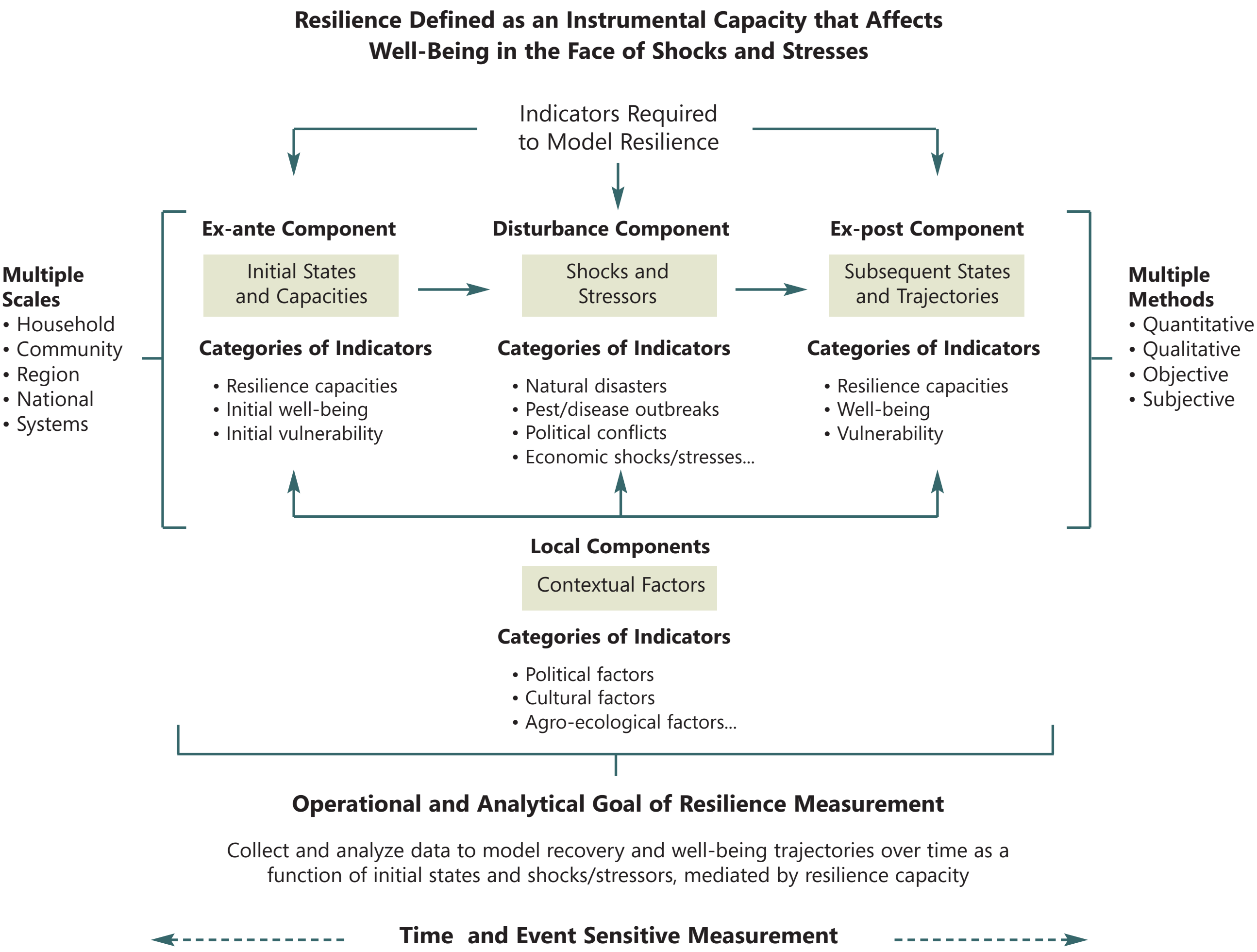
Component 2. Resilience Causal Framework

- *Practical measurement question:* How is resilience capacity positioned in a dynamic relationship that explains well-being in the face of shocks? What types of indicators need to be measured, at what points in time, at what scale and using which methods in order to measure the effect of resilience?

Causal frameworks are useful because they focus measurement activities and because they provide a potential link between the logic of interventions and the organization of data analysis that follows measurement. The development of well-specified causal frameworks involves organizing the focus of measurement as an observable sequence. A fundamental quality of a causal framework for resilience is therefore the presentation of measurement as a sequence of ordered and observable attributes, events and conditions. The presentation of resilience as a sequence of associated data collection opportunities describes the variety of indicators that need to be collected in a particular order (see Constas and Barrett 2013). A second quality of well-specified causal frameworks is that the sequence of ordered, observable events and conditions are represented as networks of testable cause and effect relationships. The opportunity to test the validity of causal networks allows one to examine the effectiveness of programmes. Such tests also help to strengthen the analyses on which claims of effectiveness are based.

Reflecting the two qualities of a well-specified causal framework, *The Resilience Causal Framework* (RCF) presented here provides a further organizational scheme in which the task of developing resilience measures can be conceptualized and implemented. In Figure 2, the key features of the RCF are expressed in the four boxed components, each of which highlights the categories of indicators needed to model resilience.

Figure 2. Resilience Causal Framework



Several features of the RCF should be highlighted. Structurally, the indicators move from ex-ante to disturbance to ex-post components, indicating a causal pathway. This pathway can be viewed as both event-sensitive and time-sensitive. Thus, resilience can be linked to disturbances and to changes in well-being measured at non-arbitrary periods (i.e., beyond simple baseline/end-line data collection plans, or seasonal collections). When the RCF is applied to actual measurement situations, it will be important to articulate how the general causal pathway and timing of data collection can be aligned with a programme-based theory of change. On a substantive level, the four boxed components emphasize the need to select and/or construct specific sets of indicators[7] as part of resilience measurement.

- **Ex-ante component** – This generates data to describe the initial state (t=1), before a shock, using categories of indicators that represent:
    - o the development outcome of interest (e.g., food security) in a way that is sensitive to the fact that well-being states are not static. The use of dynamic initial-state measurements of food security of two different households may, for example, yield the same food security score but with different patterns of food security (e.g., worsening, improving, oscillatory) observed over time;
    - o resilience capacity as a set of skills, abilities, relationships and resources held by a household, community or larger unit; and
    - o variables that influence the likelihood and consequences of risk exposure (e.g., vulnerability).

Decisions about the specific set of resilience capacities to be measured will be informed by proven or hypothetical claims about which resilience capacities are most effective in relation to a particular shock or stressor.

- **Disturbance component** – This generates data to describe the intensity and effects of various types of shocks and stressors, including:
    - o natural disasters/stressors, such as floods, droughts, earthquakes and the climate;
    - o pest and disease outbreaks that threaten agricultural production;
    - o political conflicts that directly threaten well-being and/or disrupt the systems (social systems, governments and institutions, physical infrastructure, markets) on which well-being depends; and
    - o economic shocks and stressors that affect asset holdings, asset consumption patterns, market functions, food and commodity prices, and other economic disturbances that may affect well-being.

7. The listing of indicators shown in the model for each component is meant to be illustrative rather than exhaustive. Many other indicators could be included under a given component. The selection of actual indicators will be a function of how the relationship among ex-ante, disturbance and ex-post components is modelled and how each component and inter-component interactions are affected by context.

It is important to collect disturbance information that not only records exposure to a shock but also reflects how shocks and their effects are often highly interactive. It is also useful to measure how shocks and stressors are perceived, including how they affect expectations and aspirations related to future well-being. Although aspirations are noted here as part of the disturbance component, the way in which shock exposure affects long-term aspirations should also be examined.

- **Ex-post component** – This generates data to describe the end state when the last round of measurement data are collected, using categories of indicators that represent:
    - o resilience capacity as a set of skills, abilities, relationships and resources held by a household, community or larger unit. Note: it is important to measure both ex-ante and ex-post indicators because the resources that comprise resilience capacity are often sacrificed to meet short-term needs;
    - o variables that influence the likelihood and consequences of risk exposure (e.g., vulnerability); and
    - o development outcomes using indicators related to, for example, food security, poverty or safety.

Data collection for monitoring and evaluation often follows a simple pre-post design with a single measurement taken at some point after an intervention. The timing of an ex-post (or ex-ante) measure should not simply follow a baseline, midline, end-line data collection scheme, because the relationship of these conventional moments of measurement is arbitrary relative to the shock. Rather, the decision about when to collect data could be informed by a theory of expected rate of change for an outcome of interest. As part of resilience measurement planning, it is useful to consider how long it will take for a given outcome to reach an expected level. It is also important to take ex-ante and ex-post measures at more than one point in time to increase the accuracy of non-static measures. This ensures that observed patterns of adaptation and transformation are not short-lived. Where relevant, data collection should also reflect seasonal or other normal fluctuations in indicators.

The contextual component of the RCF is an additional set of indicators focused on data needed to describe how situational factors can affect the three main components of the model: i) initial states (including resilience capacity), ii) the occurrence and experience of disturbances, and iii) the subsequent states. Although a sample of contextual factors have been cited (political, cultural, social, agro-ecological, etc.), the specific contextual factors to be included as part of resilience measurement is determined by local settings and by theories of change. This point is elaborated upon in the section below on data collection.

The bracket on the far left of Figure 2 highlights the importance of collecting resilience data at multiple scales. The systems level is the highest and most complex level at which resilience data can be collected. The far right of the framework underlines the need for multiple methods.

Component 3. Resilience Capacity Data Structure: Indicators and measurement properties

- *Practical measurement question:* What specific indicators are needed to measure resilience? What special characteristics of those indicators could help model resilience dynamics?

The development of a data structure is an important step in the process of developing measures. A data structure specifies indicators and organizes them into a structure that describes their properties. The data structure provided here for resilience capacity is organized according to i) data elements that represent resilience capacities, ii) resilience functions, and iii) measurement tactics. The data elements comprise resilience capacity categories and sample indicators. The resilience functions highlight the idea that resilience capacities may serve different functions, allowing a unit to absorb, adapt or transform in the face of a shock and stressors. The measurement tactics represent some of the methodological features of data collection.

Reflecting the general guidance presented in Paper No. 1 and drawing on the analysis of various studies of resilience (Alinovi et al. 2009 and 2010; Ciani and Romano 2013; Smith et al. 2014; Maxwell et al. 2013), Table 1 outlines a proposed data structure to inform the selection and development of indicators for resilience capacity.

Table 1. Resilience Capacities Data Structure

Resilience Capacities Data Structure: Data Elements, Resilience Functions and Measurement Tactics					
Data Elements for Resilience Capacity		**Resilience Functions**	**Measurement Tactics to Increase Validity of Resilience Measures**		
Resilience Capacity Categories	**Sample Indicators**	**Response to Shocks**	**Perspectives and Methods**	**Levels Measured**	**Time Periods and Trigger Events**
Social capital* RC-SC	• Bonding • Bridging • Linking	• Absorb • Adapt • Transform	• Objective • Subjective • Quantitative • Qualitative	• Individual • Household • Community • Higher levels	• Short term • Medium term • Long term • Event sensitive
Human Capital RC–HC	• Education • Skills & abilities • Health and wellness**				
Economic resources RC-ER	• Assets -financial & productive • Market access/mechanisms • Supply chain efficiency				
Service infrastructure RC-SI	• Roads & transportation • Water & sanitation • Medical				
Livelihood strategies RC-LS	• Food security & financial • Diversity • Adaptive				
Inst. & governance RC-IG	• Coverage • Structural integrity • Effectiveness				
Risk strategies RC-RS	• Risk exp. history/perception • Risk landscape assessment • Problem definition • Decision making & planning				
Tech. & innovation RC-TI	• Agriculture • Food handling/production • Business				
Social protection RC-SP	• Focus & type • Strategic aim • Integration & duration				
Agro-ecological RC-AE	• Soils & water resources • Cropping/grazing practices • Natural resource management				

* Aldrich, 2013
**Includes both physical and mental wellness

The indicators in Table 1 can either be combined into a single composite scale using factor analysis or incorporated into multiple regression analysis. The choice depends on the qualities of the data and on analytical capacity.

In addition to the indicators in the second column of the table, several other sets of indicators can be prioritized because of the way they are likely to affect observed resilience dynamics:

- Gender
- Ethnic/cultural identity
- Livelihood groups
- Agro-ecological zones
- Geography and other spatial factors that affect shock exposure.

These variables and others identified as relevant according to explicit inclusion criteria (i.e., reflecting variables that are consistent with a given theory of change) will help identify how resilience capacity changes as a function of variables that are important programmatically, theoretically or contextually.

Component 4. Resilience Measurement Expected Trajectory[8]

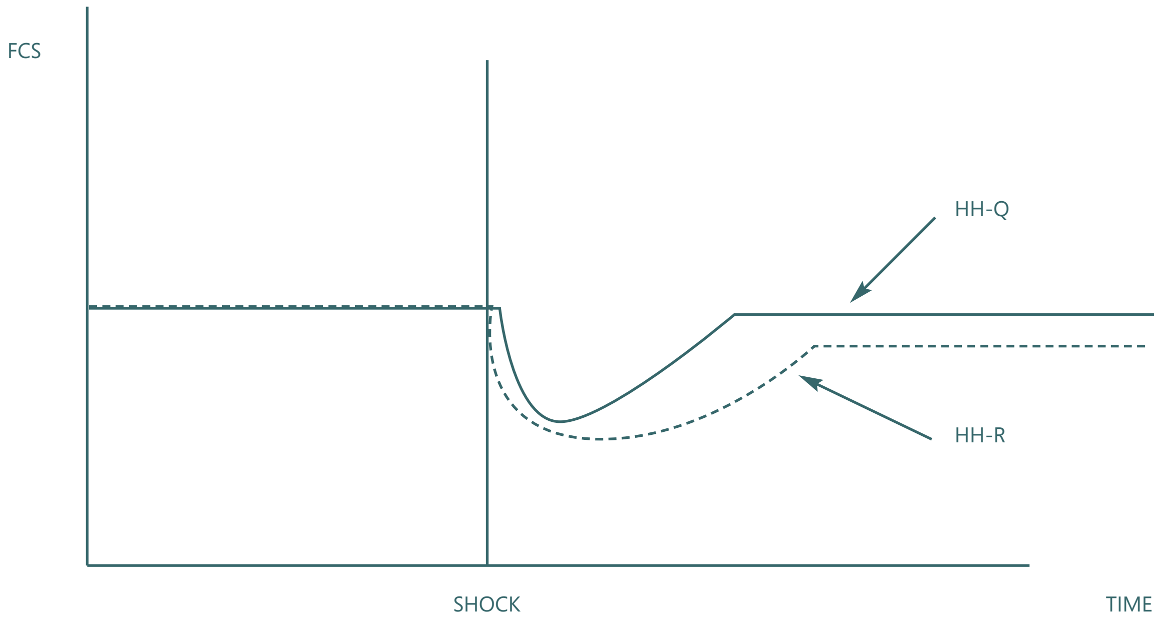
- *Practical measurement question:* What is the expected rate of change? What factors affect the rate of change of development outcomes over time, in the face of shocks and stressors, and in relation to interventions and contexts?

One of the key strategies used to collect accurate resilience data is to recognize that data collected at any point in time represent a temporal cross-section of a trajectory. The idea that observed states (e.g., well-being) are path-dependent has been well documented in resilience literature. Here, path dependency refers to trajectories that show how well-being may change over time in the face of shocks. Figure 3 illustrates this idea: it charts the food security status of two households, HH-Q (the solid line) and HH-R (the dashed line), over time.

Initially, both households have the same food security status. In the aftermath of a shock, their food security falls. HH-Q's food security gradually recovers. By contrast, HH-R's food security recovers more slowly and never fully regains its pre-shock level. HH-Q is resilient to this shock; HH-R is not.

8. This section of the paper is drawn from Hoddinott 2014.

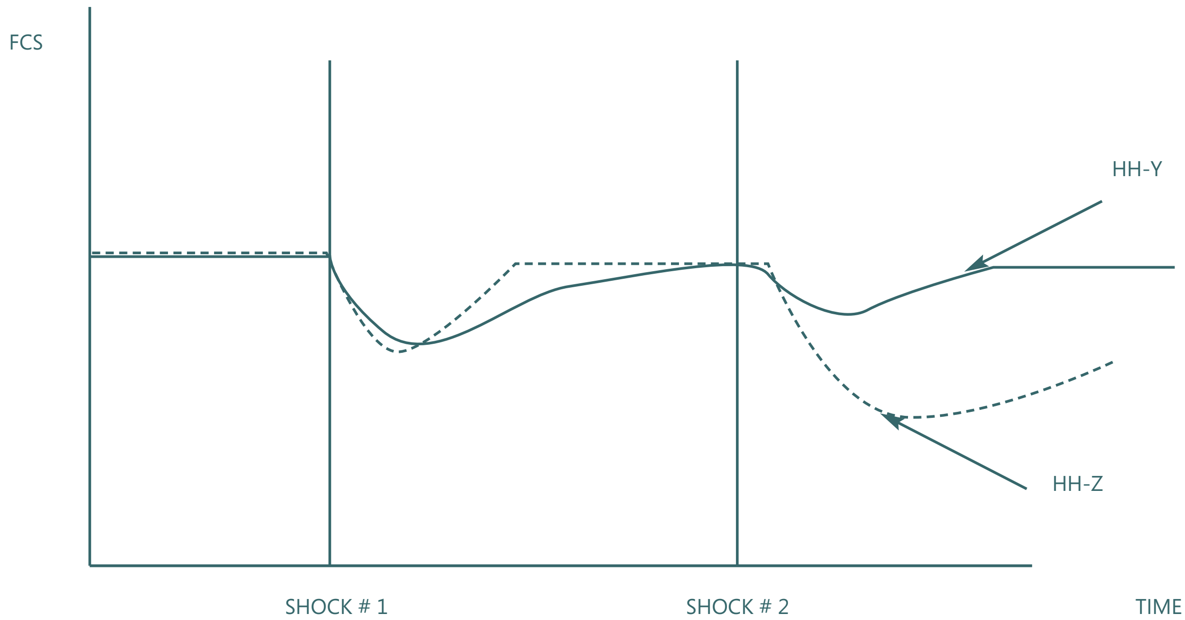
Figure 3. Food security and resilience over time



* FCS = Food Consumption Score

Now consider a variant of the paths shown above. Figure 4 shows two households that begin with similar levels of food security. Both experience a shock that causes food security to fall, and both recover and return to their pre-shock food security status, at moderately similar rates. However, when a second shock occurs, Household Y (HH-Y) recovers quickly but Household Z (HH-Z) does not. Instead, its food security falls to a new, lower level. HH-Z seemed resilient in the face of one shock but could not manage a second. The reason for this difference lies in the two households' different capacities to respond. For example, a household might be forced to sell off assets (thereby compromising future food security), or they might undertake a risky income-generating activity that could have undesirable future consequences (e.g., migrating to a distant region to work, or undertaking transactional sex to obtain money for food, thereby increase their risk of contracting HIV). Thus, they might at first appear resilient, but in fact, their future food security is endangered.

Figure 4. Food security and resilience with multiple shocks



* FCS = Food Consumption Score

Hoddinott (2006) provides an example of these processes at work in the context of the 1994–95 drought in southern Africa. In his survey of resettlement localities in three parts of rural Zimbabwe, households' principal assets were land, livestock and human capital. These assets were used to generate income from agricultural activities. In non-drought years, agricultural activities (mainly maize production, cash crops such as tobacco and cotton, and income from livestock) accounted for just under 80 percent of total household income. In 1994–95, rainfall fell by 20 to 40 percent (depending on location), more than halving agricultural incomes. Household responses to this shock differed markedly by level of asset ownership. Both econometric evidence (Owens, Hoddinott and Kinsey 2003) and conversations with farmers indicated that at least two oxen were needed for ploughing and that the absence of these severely restricted households' ability to generate income. Households with more than two oxen were three times more likely to sell at least one ox than households with one or two oxen – showing that the threat of losing a key productive asset significantly influenced household behaviour. However, women in households that did not sell oxen lost more body mass, and pre-school children in households with low oxen holdings experienced a reduction in growth rate that proved to be permanent.

The study illustrated several other issues: the difficult decisions households face following a significant income shock; the way these decisions are affected by the threat of a drought that may create a poverty trap and a general decline in well-being; and the value of examining causal assumptions more closely to understand how household responses to shocks are shaped by intra-household allocation rules.[9] Also, it is often assumed that in the aftermath of a shock, the households who suffer the most are the ones selling assets. Yet in this case, it was quite the opposite: those suffering the irreversible consequences of the 1994–95 drought were the children in households who did not sell assets.

For the purpose of collecting resilience measurement data, a number of lessons can be drawn from this discussion:

- **High-frequency measurement data** – To be sensitive to resilience dynamics, measurement data should be collected with a frequency that allows one to map the trajectory of well-being over time. Collecting data more frequently will reveal path dependencies (i.e., how well-being is an observed trajectory that changes over time) with special reference to shock exposure.

- **Operational definition of resilience and resilience pathways** – Although resilience is measured as the ability to achieve and maintain a level of well-being above an acceptable threshold, a consistent upward trajectory may indicate a 'resilience pathway' even in cases where acceptable levels of food security, poverty, etc. have not been reached.

- **Integration of intervention planning and trajectories** – Insights gained from data on how well-being fluctuates over time in the face of shocks could help identify optimal points of entry for an intervention.

Component 4 also raises questions about whether resilience capacity should be measured against a threshold (i.e., a minimum acceptable state of food security or well-being) and/or according to a trajectory (Barrett and Constas 2014). These decisions are important for calibrating measures and for making claims about the effectiveness of a given intervention.

Component 5. Resilience Measurement Data Collection Methods

- *Practical measurement question:* What types of data collection tools and perspectives are needed to obtain accurate data on resilience?

In line with the recommendations provided in Paper No. 1, the following elements would strengthen measurement data collected for resilience:

- **Analysis of contextual factors** – The focus on contextual factors requires one to consider how local conditions, situations and the features of settings affect the capacity to deal with shocks and stressors and/or directly affect the outcome of interest.

9. Very loosely, these can be described as: 'who does what', 'who gets what' and 'who decides who does what and gets what'. See Haddad, Hoddinott and Alderman (1997) for a lengthier treatment.

- **A systems perspective** – The tasks of conceptualizing, measuring and modelling resilience can be informed by a systems perspective. It is important to construct measures that are sensitive to the highly interconnected sets of relationships that affect development outcomes in the face of shocks and stressors.

- **Use of multiple data collection methods** – Resilience measurement requires quantitative and qualitative data collection methods. The strongest measurement designs will identify ways to integrate both methods to deepen descriptions and strengthen inferences.

These three features of resilience measurement are described in more detail in the sections that follow.

Analysis of contextual factors – Contextual factors can mediate and moderate the effects of interventions and programmes that aim to affect development outcomes. In general, context refers to the set of geographical, social, cultural, political and historical factors that influence how interventions are implemented and how effects are analysed. This could be anything from national political corruption, land elevation or agro-ecological zone to household traits not considered in resilience programming (e.g., certain demographic variables or attributes). Contextual variables are sometimes referred to as background variables that describe the properties of the settings and characteristics of populations that can affect observed outcomes. There is no rule to decide what should be counted as a contextual factor. This is because background variables are defined according to the aims of the intervention and the way in which one or more outcome variables are affected by context. For measurement, context should be described in practical terms as part of an intervention's theory of change and in technical terms as part of a data collection protocol.

One of the challenges of discussing context is coherence. How might the various aspects of context be expressed in a way that conveys the interdependencies among sources of contextual influence? A systems perspective, as a tool for organizing multiple influences, provides a good response to this question.

A systems perspective – It has been argued that development outcomes, such as food security and economic well-being, are the result of a complex series of relationships that can be understood through a systems perspective. Ecologists have long asserted the need to approach questions about resilience in this way (see Holling 1973). Concepts that are central to resilience in development have been defined and subjected to empirical testing by ecologists (see Gunderson, Allen and Holling 2010).

Many different scientific articles have highlighted the benefits of adopting the concept of resilience as a framework for analysing empirical problems (Carpenter et al. 2001; Berkes et al. 2003; Gunderson and Folke 2005; Walker et al. 2006). Certainly many would agree that one of the most useful characteristics of resilience is its ability to help frame problems within a systemic approach and to think 'holistically' – something that is particularly relevant in the context of development, for several reasons.

First, a systems approach is useful because many of the shocks that affect households and/or societies are becoming increasingly covariate, affecting groups of households or even entire communities (World Bank 2000; Heltberg 2007). Wherever the vulnerability of individuals is intensified by their social and economic dependence on others who appear, themselves, to be affected by the same disasters and shocks, the holistic (systemic) nature of resilience and its emphasis on the interdependency of distinct system components is particularly helpful. Good examples of covariate shocks are climate-related shocks, natural disasters or economic crises (e.g., Carter et al. 2007).

The resilience approach is therefore useful because it gives a systems view of social-ecological interactions, which appears necessary to understand the links between human systems, ecosystems, and shocks and trends. The multi-scalar view of resilience can also help identify the relationship between (and ideally, the complementarities of) different types of interactions, as well as the thresholds of different types of systems. It is important to consider thresholds or tipping points that when crossed may lead to systems-state change. For example, many innovations and conflict studies show how thresholds in human behavioural change are crossed when critical mass is achieved. It therefore helps to identify some general characteristics that make a system resilient in a context of uncertainty and exposure to multiple types of risk. As such, a systems portrayal of risk may shed light on the multiple sources of vulnerability that can affect households or society at different scales (Wisner et al. 2004.

Second, adopting a systems approach helps explain why many of the processes and dynamics that affect people and/or their environments occur across scales, from local to global (Adger et al. 2005) and are often characterised by feedbacks (Folke 2006). In practical terms, if resilience is understood as a concept related to systems, those who are in a position to affect change (e.g., policy makers, program developers) should be better able to evaluate the likelihood and desirability of shifts or transitions among different system configurations. Carpenter et al. (2006) speak of the importance of cross-scale effects in their reflections about research needs in relation to Socio-economic Status (SES) and the Millennium Ecosystem Assessment. They cite the example of the loss of buffering coastal ecosystems that has eventually exposed extensive stretches of coastline to catastrophic damage, such as the 2004 Asian tsunami or recurrent hurricanes in the Gulf of Mexico.

In the context of rural livelihoods, resilience and its emphasis on systems and holistic thinking also has some resonance in relation to natural resources and the environment. Poor people are recognized as depending more heavily on natural resources (Reddy and Chakravarty 1999; Beck and Nesmith 2001; Béné et al. 2009). Thus, the resilience of a community is inextricably linked to the condition of the environment and the status of its resources. Emphasizing this social-ecological dependence helps define (or redefine) the vulnerable groups (thereby improving intervention targeting). It may also help to design better 'green' public works programmes for environmental rehabilitation or natural resource conservation (such as reforestation and soil conservation measures, e.g., Kuriakose et al. 2012).

The application of systems approaches to resilience measurement has a number of important implications. Embracing a systems approach implies that measurement must occur on multiple scales (temporal, spatial, jurisdictional, institutional) and using multi-method approaches.

As noted in Paper No. 1, a systems perspective in analysing resilience and its determinants leads to consideration of systems thinking and multiple scales or levels of scales in resilience measurement. For each of the four components – ex-ante, disturbance components, ex-post and contextual components – the important drivers of resilience at the level of interest may occur at different levels (or scales) of the system. Note that 'scale' and 'level' of measurement are terms that are used differently by various disciplines.[10] In this analysis, they are used interchangeably.

For example, the (ex-ante or ex-post) measurement of well-being is often conducted at individual or household level, whereas resilience capacities may include factors measured at different levels of the system. These levels may depend on whether the factors are related to vulnerability or resilience: soil quality (vulnerability) could be measured at ecological level, while the capacity for collective action (resilience) might operate at community level. In other cases, resilience measurement is directed to subnational or national level, meaning that interventions and measurements are captured and monitored at regional, district, ecological, community or household level.

Similarly, the disturbance component can be measured at household level, though this measure typically reflects the household respondent's subjective experience of exposure. This may differ from the actual hazard exposure, which is best measured by environmental data (e.g., land condition, rainfall). Of course, hazards also have different geographic boundaries and different scales (depending upon their coverage). However, sensitivity to exposure should be measured at household level, as this is the primary unit of analysis. Chronic stressors are often political, environmental and cultural, which are frequently regional but can be at higher or lower levels of the system. For example, cultural values that encourage behaviours that erode the natural resource base or hinder the empowerment of women can have a negative impact on resilience.

The important point here is to analyse the levels at which the most critical factors influence a particular measurement component. In some cases, these factors could be pre-identified through secondary analysis of data, for example, time series analysis or the re-analysis of large-scale household surveys such as the Living Standards Measurement Surveys. Alternatively or in parallel, formal qualitative techniques can be used to identify the key factors operating on a given system. Importantly, this multi-scale measurement requirement also has consequences for the frequency of survey/monitoring. Empirical sciences – particularly terrestrial and marine ecology – have shown that there is a form of linear relationship between spatial and temporal scales: lower-level dynamics and processes usually operate at higher frequencies than larger-scale phenomena (Steele 1989; Levin 1992). For instance, changes in oceanic circulation systems usually occur over longer time scales (generally decades), than the evolution of individual organisms (seasons or years) (Haury et al. 1978). In our case, dynamics important at individual level (e.g., changes in well-being, food security or asset levels) may need to be recorded relatively frequently (e.g., monthly), especially to capture their change in relation to a particular shock. But changes occurring at higher level (e.g., changes in community attitudes towards collective action or changes in natural resource

10. Different domains of interest to resilience measurement may have differing spatial boundaries or boundary mismatch. This may occur, for example, when administrative and agro-ecosystem boundaries are not aligned, which is usually the case.

degradation) may have to be monitored less frequently (e.g., annually or bi-annually). These considerations have important consequences for recommended approaches to resilience measurement.

Use of multiple methods – Multiple methods are needed to measure variables that determine or capture resilience capacity. This is because of the dynamic, contextualized and multi-level nature of resilience and its determinants. There are two basic classes of technique: qualitative and quantitative. Qualitative methods include focus groups, key informant interviews, participatory impact evaluation and techniques for eliciting rankings from local populations. Qualitative information takes the form of words or narrative that cannot be expressed meaningfully in numeric format. This type of information does not often lend itself for inclusion as modules in questionnaires. However, it can be used well in a variety of ways in resilience measurement. It can be used to develop locally relevant resilience measurement indicators for quantitative assessment. It can also help identify key local drivers of resilience among populations. Qualitative methods are often employed to measure certain variables and behaviours such as conflict dynamics, local resilience mechanisms and aspects of social capital. They are also used to generate indicators that are later incorporated into quantitative methods (see below) or that better focus measurement strategies on the most important determinants or manifestations of resilience.

Social relations are key to determining resilience, particularly for households, but also for communities, whether they face idiosyncratic or covariate risk. Social relations are extremely difficult to capture solely with quantitative information, and the impact of social relations on resilience and livelihoods or poverty outcomes is extremely difficult to predict in the absence of good qualitative information. Qualitative and subjective information is critical to answering questions about *why* some households or communities are resilient and others not (as opposed to *whether* they are resilient). This information can help explain behaviour and decision-making processes by revealing motivational or cultural value systems and beliefs (Maxwell 2013).

Quantitative methods are usually associated with population or spatial probability sampling, where the goal is to generate estimates of populations or the characteristics of environmental or socio-environmental systems, including measuring change over time. Quantitative work seeks to draw inferences about household or community resilience and to judge spatial and geographic counterfactuals scientifically.

It is important to distinguish qualitative and quantitative methods from objective and subjective measures. Subjective and objective measures can be used in either quantitative or qualitative methods.[11] Subjective measures are any form of respondent rating or assessment, but in resilience work they are typically associated with coping behaviours, risk exposure and social capital. Objective assessment methods are those that do not rely on respondent judgements. These include environmental data sourced from satellites, some types of anthropometric assessments, observable assets and surveillance data on mortality.

11. See Maxwell (2013) for a more extended discussion on the use of subjective and qualitative data.

Qualitative and quantitative assessment methods are often used together to measure resilience and its determinants. This combination may improve resilience measurement by identifying the most important factors to measure and validating measures through the convergence of evidence. Sometimes these methods are used iteratively or sequentially to develop an assessment framework for resilience measurement. In this case, depending upon the availability of secondary data, the secondary analysis of quantitative data (surveys, administrative records) may be used to identify key drivers and manifestations of resilience and vulnerability. When secondary data are not available, or immediately after reviewing available data, formal qualitative methods may be the first application of measurement used to identify potential indicators in the framework. Quantitative measures can then be developed and tested, and qualitative methods can be used to interpret the quantitative findings. This approach is one of the most commonly used in the field to date.

An alternative approach utilizes qualitative methods to capture attributes related to resilience, often community factors collected from key informant interviews or focus groups. These community traits can then be summarized quantitatively across communities, or they can be represented as indicator variables and integrated with household data to develop a multi-level data set.

These methods also can be used to calibrate measurement across time. For example, between ex-ante and ex-post measures, a combination of qualitative and quantitative methods can be used to identify the aspects of stressors and shocks that are most closely related to vulnerability and resilience, as well as to identify anticipated capacity, vulnerability and well-being outcomes.
The validity of difficult-to-measure variables around social capital, for example, can be improved using convergence-of-evidence approaches where qualitative methods applied at community level are corroborated with subjective information from household surveys.

Objective and subjective measures can be used in complementary ways to better understand perceived risk as a function of risk exposure, a potentially important driver of resilience and vulnerability. For example, covariate risk exposure from natural hazards may be best measured quantitatively from objective environmental data, while ‘sensitivity to hazards’ exposure might best be measured through subjective data such as perceived risk and coping behaviours, to differentiate between risk exposure and perceived risk.

The use of different techniques also depends on data availability and the specific objectives of the resilience measurement exercise. Quantitative data include retrospective time series data, household surveys and systematically collected data that can be enumerated at higher levels in the system (communities, districts). Qualitative methods can be used to produce data that can be quantified, albeit with great care. It is vital to ensure that the strengths and weakness of quantitative and qualitative data are described and understood.

Component 6. Resilience Measurement Estimation Procedures[12]

- *Practical measurement question:* How might data be analysed to draw inferences about the effect that resilience capacities have on development outcomes in the face of shocks and stressors?

This component of the common analytical model seeks to frame resilience measurement in the form of a typical regression model. As noted earlier, there are many models of resilience in circulation. The main benefit of an analytical model is that it provides an explicit approach to translate ideas into empirical content or data. The aim of an estimation model is to show how variables might be related to each other. Thus, a key part of an analytical model is the formalized, symbolic expression of relationships to be tested. In general, these expressions specify a causal relationship in which a given variable or set of variables (predicted or dependent variables) is seen as the functional outcome of another set of variables (predictor or explanatory variables). Expressions of this kind are variously referred to as functional forms, specifications, estimation models, formulae, prediction models, or simply models.

In Paper No. 1, and in the introduction to this paper, a simplified version of a resilience estimation model was presented. This initial simplified version is now elaborated upon in three ways. First, the original model, referred to here as the *simplified model,* is modified to demonstrate the time-sensitive quality of resilience and to highlight the need for both objective and subjective measures. Reflecting elements of the common analytical model, this creates a more complex estimation model: the *Time-Sensitive Model with Subjective Measures*. In this initial discussion of estimation models, the original model and the time-sensitive resilience model are presented without using econometric conventions. Then, the set of assumptions used to construct an estimation model for resilience are presented. Finally, a more fully developed model with more precisely defined variables and an econometric formulation is presented. This final presentation of the estimation, presented as a *functional form*, is offered as an illustration and as a way to highlight the value of specifying models that can be empirically tested.

Modification of the simplified model. *A simplified = model* shows the function of resilience capacity as a variable that might exert its influence in relation to other variables that affect the well-being of a household, community or other unit affected by shocks and stressors. The function was expressed in the following simple form:

Simplified estimation model:

Food security = f (vulnerability, resilience capacity, shocks)

In addition to demonstrating the instrumental value of resilience capacity, the *simplified resilience model* was introduced to indicate that resilience should be defined both in ordinary language and as a formula.

12. Although the aim of this section is to provide a reasonably general presentation, the description of estimation procedures for resilience measurement is the most technical aspect of the common analytical model. Readers who are less interested in estimation procedures may elect to proceed directly to section four, *Conclusions*.

To reflect the temporal sensitivity principle presented in Paper No. 1, and as preparation for a more elaborate econometric presentation, a time dimension may be added to the *simplified resilience model.* A time dimension can be included using a subscript t (t=1, 2, 3,..n) indicating that multiple measurements are taken over time. The first measurement is taken at *t*=1, the second measurement is taken at *t*=2 until the last measurement when t=n. The modified version of the *simplified resilience model*, which includes a time dimension with both subjective and objective measures of shocks, is as follows:

Time-sensitive model with subjective measures:

$$\text{Food security}_t = f\,(\text{vulnerability}_t, \text{ resilience capacity}_t, \text{ shockt}^{O,\ S})$$

The subscript t for food security means food security at time t, such as baseline data collected prior to an intervention. The change in food security may be measured as the difference between food security at *t* and food security at *t*+1.[13] The first predictor variable, vulnerability, shows how vulnerability changes over time (*t*=1, 2, 3,...n), with observed decreases in vulnerability possibly attributed to resilience. The second predictor variable, resilience capacity, is a composite of variables that are hypothesized as ensuring that a unit (e.g., household or community) does not suffer adverse consequences in the face of shocks and stressors. It represents the set of resources that enable the unit to prepare for and/or respond to the effects of a shock. The time-sensitive component is included here to reflect how the dimensions that constitute resilience capacity may change over time. Long-term well-being may, for example, be compromised to meet short-term needs. The third predictor, shock, represents one or more events or conditions that threaten the well-being of large numbers of people (covariate shocks) or smaller, more isolated numbers of people (idiosyncratic shocks). The O, S for the shock term superscript indicates that both objective (data on occurrence) and subjective (data on perceptions of shocks and stressors) measures should be included. The time subscript for shocks suggests that both the objective and subjective features of the shocks change over time.

Framing resilience capacity within a formal estimation model. Considering that “resilience is the capacity that ensures adverse stressors and shocks do not have long-lasting adverse development consequences” (Paper No. 1: p. 13), two observations set the stage for introducing an illustrative estimation model. First, the specific resilience capacities used in an estimation model can be indexed to food security, poverty or any other well-being concept that represents a development outcome of interest. Second, resilience, unlike related concepts (e.g., vulnerability), emphasizes the long-lasting effects on the outcome variable as it captures a household’s capacity to absorb, adapt and transform in response to shocks.

13. In the case of an impact evaluation with an intervention, the estimation procedure might use a difference-in-differences method where the change in food security would involve a further comparison of changes in food security observed between an intervention condition and a control condition.

By examining how an outcome changes over time in the face of shocks, the dependent variable in the estimation model measures the resilience of a household and of larger units that may affect the household. Note that resilience is not only a genuinely dynamic concept, involving the process of preparing for and responding to shocks, it is also defined with reference to the "long-lasting" consequences of a given shock.

The estimation model, and the analytical model from which it is derived, must be able to capture all possible pathways to well-being in the face of shocks. These pathways may be very different, even across households living in the same context. As a result, the estimation model must be able to express the causal relationship linking risks and outcomes (the risk chain) and account for heterogeneity.

The estimation model for resilience analysis should be general enough to be applied in different contexts and flexible enough to be context-specific. Consistent with the principles of resilience measurement noted in Paper No. 1, the resilience model should be indexed to a specific well-being outcome. This means that the dependent variable should be an indicator of well-being status, such as food security. The specific indicator to be used depends on the objectives and scale of the analysis. Households would seem to be the most suitable entry point for the analysis of resilience to food insecurity.[14] If this is the case, a suitable welfare status indicator is household food consumption at different points in time, or changes in food consumption between two points in time. However, there is no reason to restrict the analysis to household food consumption: any household welfare indicator could be used (e.g., nutritional or health status) (cf. Hoddinott and Kinsey 2001).

Adopting a household perspective does not mean disregarding the importance of the relationships between households and the broader system they belong to (e.g., the community or district). Rather, this means acknowledging that systems comprise hierarchies, and that each level involves a different temporal and spatial scale. Therefore, if the analysis level is different, say food security at community or higher hierarchical level (e.g., district, province, state, region), the dependent variable indicators may change (e.g., the proportion of food-insecure population, the food security gap, or the average daily energy consumption in the population).[15]

This also means acknowledging that the broader system helps determine household food security performance, including resilience to food insecurity (this is the 'setting' in the risk chain). Operationally, this means that the characteristics of the broader system that the household belongs to should be explicitly accounted for in the analytical framework and in the model.

14. The household is the unit within which the most important decisions to manage both ex-ante and ex-post risk are taken. This includes how risk-related decisions affecting food security, are made: e.g., what income-generating activities to engage in, how to allocate food and non-food consumption among household members, what strategies to implement to manage and cope with risks.

15. As will be clear from the discussion below, the estimation model needs to be modified to account for these changes in the dependent variable. For instance, a higher level of analysis and bigger covariate, as opposed to idiosyncratic, shocks would require modification of the model. Usually, this also translates into a longer timeframe for the analysis. However, the longer the period of analysis the higher the likelihood of compounding effects from multiple shocks, which can complicate the task of identifying causal mechanisms.

The timeframe for the analysis also depends on the analytical objectives: specifically, it depends on the level of the analysis and on the livelihood strategies adopted by a given household (which in turn define the risk landscape it lives in and the options available to manage risks). Indeed, the choice of timeframe is embedded in the definition of resilience, which focuses on the "long-lasting" adverse consequences of shocks. Generally speaking, the longer the time period covered by the analysis, the better for assessing these consequences (e.g., the ability of the household to recover [or achieve] a welfare status above the established normative threshold).[16]

The issue of how short the minimum timeframe should be for a meaningful analysis depends on the household livelihood strategy. The strategies used by pastoralists or farmers are completely different from those of rickshaw drivers or urban wage earners in terms of the speed of income generation and asset building, as well as in their temporal patterns (e.g., seasonal or not seasonal). Operationally, this means that i) the model should explicitly control for heterogeneity in livelihood strategies and their risk profiles, and ii) the timeframe should be long enough to give the household a chance to recover (e.g., three to five complete production cycles). More often than not, this means considering an analytical timeframe that spans many years.

The closest reference for a quantitative analysis of resilience that builds on economic work is vulnerability analysis. According to Hoddinott and Quisumbing (2010), there are three main approaches to assessing vulnerability: vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU) that minimizes future well-being, and vulnerability as uninsured exposure to risk (VER). All these approaches are econometric models that estimate a welfare measure – usually household consumption and variants of it.

Measures of VEP and VEU estimate vulnerability as the likelihood that realized consumption will fall below a normative threshold. These approaches measure household vulnerability over all individual households, yielding a measure of aggregate vulnerability. VER does not estimate probabilities; instead, it assesses whether observed shocks generate welfare losses. VER measures are ex-post assessments of how far a negative shock causes a household to deviate from its expected level of welfare.

Recalling the definition of resilience introduced in Paper No. 1, the VER provides a suitable basic analytical framework to assess resilience, especially when using available data sources such as the Living Standards Measurement Survey data and related household data sets. The basic estimation procedure is defined below, along with suggested enhancements based upon the availability of richer data sets, which are coming online for the purpose of measuring resilience.

The description of the functional form of an estimation model for resilience presented in the next section is written for audiences interested in the statistical and econometric aspects of resilience measurement. The readers who are more interested in the conceptual treatment of resilience measurement may skip to the concluding section of the paper, section four.

16. However, the longer the period of analysis the higher the likelihood of compounding effects from multiple shocks, which can complicate the task of identifying causal mechanisms.

Estimation model for food security using resilience capacity. A basic model is defined below, where *h* denotes the *h*-th household living in village *v* at time *t*. As the dependent variable, food consumption[17] ($\Delta \ln FC_{htv}$) might be defined as the difference between log food consumption between t and t+1, i.e., the rate of growth of food consumption, or other well-being outcome, over the period under consideration. Then the impact of the shocks occurring between *t* and *t*+1 on food consumption of the h-th household can be estimated according to the following relationship:

Functional form estimating food security using resilience capacity:

$$\Delta \ln FC_{hvt} = \sum_i \alpha_i CS(i)_{vt} + \sum_i \beta_i IS(i)_{hvt} + \sum_{vt} \delta_{vt} RC_{hvt} + \gamma X_{hvt} + \theta Z_{hv} + \Delta \varepsilon_{hvt}$$

where CS_{vt} is a vector of covariant shocks occurring between t and *t*+1. The term $IS(i)_{htv}$ represents a vector of idiosyncratic shocks over the same period (including both objective and subjective elements as noted above); RC_{htv} is a vector of categorical and continuous variables[18] that indicate the resilience capacities employed by a given household at time *t*; X_{hvt} and Z_{hv} are, respectively, time-varying and time-invariant household characteristics (or characteristics from possibly higher-level aggregates); and $\Delta \varepsilon_{hvt}$ is a stochastic error term.

The estimated values for α and β identify the magnitude of the impacts of covariate and idiosyncratic shocks, respectively. The impacts of both covariate and idiosyncratic shocks are countered by the effects of private resilience capacities (i.e., from within households) and public responses (i.e., from social programmes, resources and policies).[19] By quantifying the impact of these shocks, this approach identifies which risks would be an appropriate focus of policy and estimates the effect of resilience capacities. Moreover, considering the well-known asymmetric impact of positive and negative shocks, it may be useful to disaggregate the shock variables into positive and negative shock components (Dercon and Krishnan 2003).

The econometric estimation of the model above can be best performed if panel data are available. Here it is important to recall that resilience measurement requires a comparison between ex-ante and ex-post states with resilience capacities as a mediator. Using cross-sectional data would suggest two key assumptions: first, that cross-sectional variance can be used to estimate the inter-temporal variance; and second, that there is no correlation between observed shocks and unobservable household characteristics. Alternatively, if repeated cross-sections drawn from the same sampling frame are available, cluster panels can be created, though this will only capture the inter-temporal variation of a representative household per cluster. This may not be appropriate if household characteristics vary widely across clusters. Panel data analysis allows the analysis of changes at individual level. If estimates are derived through fixed effect regression, one can control for unobservable time-invariant characteristics of households and communities. The types of panel data sets needed for this work are not routinely feasible for applied field

17. For the purposes of illustration, food consumption is used as an outcome representing food security. Any development outcome or other indicator of food security may be inserted as the outcome of interest.

18. This variable can also be disaggregated into the absorptive, adaptive and transformative capacities that represent the multi-dimensional nature of resilience capacity.

19. The impacts of these private and public responses may be quantified if the variable RC is appropriately disaggregated.

assessment and monitoring. This argues for the judicious use of secondary data sources to identify key resilience drivers, which should be monitored over time in project environments.

Practitioners and policymakers want to know which segments of the population are less resilient than others, so they can improve targeting. The population strata showing a larger impact can be identified by modifying the equation and introducing an interaction term between the shock variable and a vector of dummy variables indicating household characteristics (Harrower and Hoddinott 2005; Skoufias and Quisumbing 2005). In this specification, the sign and size of the coefficient of the interaction term identifies the extent to which there is higher or lower covariation between the shock and consumption changes in the group of households with this specific characteristic relative to the reference group of households without this characteristic. Along similar lines, the Student's *t*-value associated with this coefficient allows one to test whether this difference is significant.

Generally speaking, a non-resilient household is one that shows poor risk management in the face of negative shocks (Dercon and Krishnan 2003). This feature can be used as a strategy to assess what makes a household non-resilient. Shocks are included as determinants of food consumption change in the equation. It is then straightforward to identify sources of resilience/non-resilience by looking at the magnitude and statistical significance of risk variables' estimates. In order to design appropriate social protection instruments, one needs to examine the existing capacities that households use to cope with idiosyncratic and covariate shocks. This can be done by regressing risk management mechanisms (capacities) on shocks and household characteristics (Skoufias and Quisumbing 2005). By allowing shocks to interact with fixed household characteristics, one can also determine whether different types of households are more or less likely to use a given set of capacities to manage risk. Furthermore, cross-tabulating the responses to shocks (private and/or public) to welfare impacts (significant/non-significant) provides information on the efficacy of these risk management capacities. This can be used by policymakers to identify intervention priorities (Hoddinott and Quisumbing 2010). The information can be further disaggregated by household characteristics as a way of determining how effectively public responses are targeted.

Estimation models, inference and qualitative methods. Although the task of specifying an estimation model requires a range of inputs, there is a tendency to view such modelling as an exercise in quantitative analysis. To provide a more complete picture, it is useful to think about the inferential objective that is served by specifying and testing estimation models. Estimation models of resilience are important because, with an associated quantitative expression, they clarify the relationship between a set of variables that are meant to predict an outcome in the face of shocks and stressors, and outcome of interests such as food security. An estimation model can help identify the strength of these relationships, and it helps describe the degree to which such relationships converge or diverge in a given population. However, estimation models do not provide highly detailed descriptions of local contexts. Quite often, they explain a relatively small – albeit statistically significant – portion of the variation in the variables they are meant to predict. While estimation models provide a technically defensible way of estimating the effects of intervention, they do not offer special insights into how people perceive and experience an intervention as a part of their everyday lives. There are some questions for which estimation models are well designed, and others for which qualitative methods are more appropriate. As a general rule for designing resilience measurements, inferences will be strongest and descriptions most complete when both qualitative and quantitative methods are employed.

IV. Conclusion

Resilience is a new concept for development and one that continues to be applied as a potential solution to a broad range of problems. The introduction of a new orienting concept offers the opportunity to reinvigorate and more effectively focus work within a given field. A new concept, such as resilience, can provide a different lens through which to explore policies, formulate interventions, and plan studies. However, the opportunity to make progress on a new concept is often hampered by the tendency to represent and/or measure the concept based on a logic that is largely unspecified or opaque. The articulation of a common analytical model can facilitate progress by promoting transparency of the logic upon which measurement depends. The opportunity to achieve progress that is scientifically defensible is enhanced by the presentation of a common analytical model, even if the model itself is not widely accepted. Uniform acceptance of ideas is not a hallmark of science. On the contrary, science depends on open debate and active dissent (see Popper 1962). In the interest of advancing a scientific approach to resilience measurement, a common analytical model is introduced. Two benefits of a common analytical model for resilience measurement are that strategies for developing measures will be transparent and openly debated, and that arguments around resilience measurement may be brought into sharper focus.

Comprised of six components, the common analytical model introduces a set of issues upon which resilience measurement may be based. The Resilience Causal Framework illustrates a basic causal pathway that identifies the points at which data should be collected to predict the food security (or other well-being outcome) of households, and possibly other units (e.g., communities), in the face of shocks and stressors. The model defines resilience capacity as a multi-dimensional, multi-level mediator of shocks and stressors. It draws attention to the need to collect data on initial states, shocks, subsequent (post-shock) states and contextual influences. The model also suggests how to construct resilience capacity measures, proposing ten categories of indicators. The discussion of methods covers the importance of multiple methods (quantitative and qualitative), as well as objective and subjective indicators. Finally, from an analytical perspective, the paper describes estimation models that might be used to assess the impact of resilience.

In closing, the common analytical model is useful because it provides a shared point of reference to develop and apply measurements across varied contexts. To that end, this paper proposes a common analytical model for resilience measurement that is both broadly applicable and technically sound. The model is broadly applicable because it is general enough to be adapted across a variety of settings and interventions. It is technically sound because it provides an identifiable causal framework for resilience and recommends perspectives and procedures to guide measurement. The next stage of work on resilience measurement involves generating an array of data sets that can be used to describe how resilience capacity is distributed across different settings and populations and to test hypotheses about the effects of related interventions. A systematic review of data on resilience will lead to improved measurement. The analysis of data, obtained from multiple studies of people who live in shock-prone contexts, will also allow an assessment of how much value resilience capacity adds to the effectiveness of development and humanitarian strategies.

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VI. Annex: Review of Selected Models for Measuring Resilience

As interest in resilience grows among agencies, donors and other stakeholders, so too does the need for agreement on a conceptual framework that provides a comprehensive picture of the specific elements that contribute to resilience.

A resilience conceptual framework should help users understand how shocks and stressors affect livelihood outcomes and household well-being. It should also help identify the key leverage points to be used in developing a theory of change, which in turn informs programming designed to enhance resilience (Frankenberger et al. 2014). Ultimately, a conceptual framework for resilience assessment can highlight the types of indicators that might be used to determine whether households, communities and higher-level systems (e.g., national, regional, global) are on a trajectory toward greater vulnerability or greater resilience (DFID 2011; Frankenberger et al. 2012).

FAO Conceptual Framework

Resilience thinking has evolved considerably over the last seven years. Since 2008, FAO has been developing a framework for measuring resilience (Alinovi et al. 2009).

FAO's methodology to measure resilience to food insecurity identifies and weights the different dimensions of household resilience through an econometric structural equation model. The results of this analysis inform programme investment, targeting, design and impact evaluation. The methodology was first applied in the West Bank and Gaza Strip to measure household resilience to food insecurity. It was later applied in other countries as a:

- **Diagnostic tool** (Ethiopia, Kenya and the Sudan) to empirically measure household resilience to food insecurity according to their different livelihood strategies; and as an

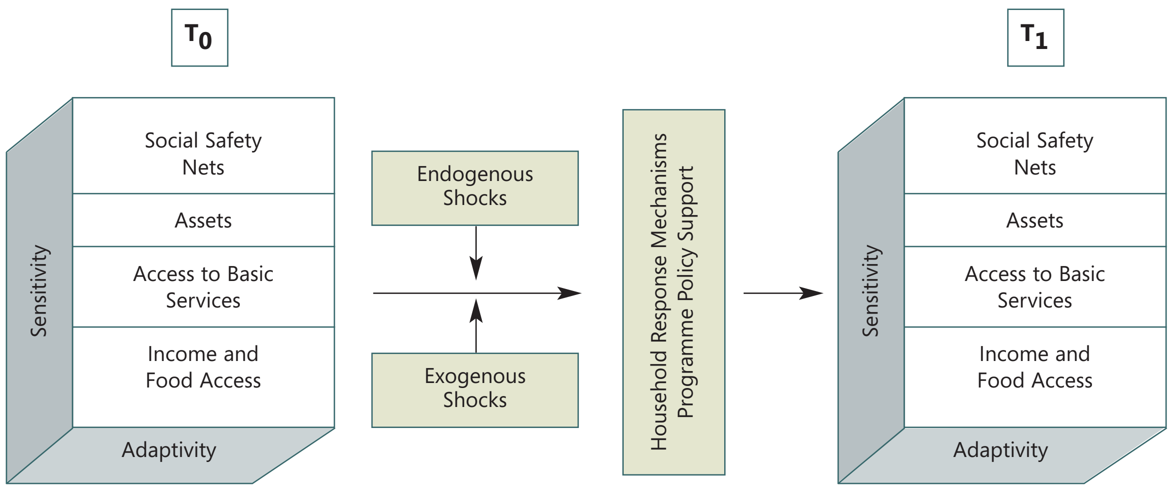
- **Impact evaluation indicator** (Somalia, South Sudan and the Sudan) to improve the design of future interventions and related accountability mechanisms.

In FAO's analytical framework, resilience explains why one household returns to a desired level of food security while a similar household does not. FAO's model, therefore, explains the interaction between shocks and their effects on households, with resilience accounting for the difference in outcomes between two similar households exposed to the same shock. For FAO, the outcome examined is food security.

According to the model, the outcome for a given household is a function of (i) the probability of being affected by a natural crisis due to the geographical location of the household; (ii) the probability of suffering from a shock due to a particular set of household characteristics that determine a household's livelihood; and (iii) the resilience of the household.

In the most recent update used in Somalia (FAO 2014), the model considers resilience as a latent variable made up of multiple components (Figure 5). Each component is a latent variable because it cannot be observed directly. The components are agricultural assets, non-agricultural assets, agricultural practice and technology, income and food access, access to basic services, social safety nets, adaptability and sensitivity.

Figure 5. FAO Resilience Conceptual Framework used in Somalia



Source: FAO 2014

Initially, FAO's model used factor analysis to calculate the latent variables (e.g., in Kenya, and in the West Bank and Gaza Strip). Variables were selected that could be used as a proxy for each dimension of resilience.

Recent exercises have used exploratory factor analysis (i.e., the measurement model is a structural equation model). Factor analysis assumes that the residual errors (unique factors) are uncorrelated with each other and are uncorrelated with the common (latent) variable. For food security analyses, the latter assumption cannot be accepted, because the probability of intra-dimensional correlation is high. Thus, structural equation modelling has been adopted, which includes correlation between residual errors. Although this method requires a greater number of computations than previous exercises, it allows for model calibration until a satisfactory level of goodness-of-fit is achieved.

The study conducted by the University of Florence expands on the original approach developed by Alinovi et al. (2009) by applying it to a specific shock event. It measures the food security resilience of rural households affected by Hurricane Mitch in Nicaragua in 1999, and it produces a single agricultural resilience index, which is itself a composite index made up of 11 latent variables estimated through factor analysis (Ciani and Romano 2013). Though based on the FAO model, it adds certain household characteristics, as well as social, economic and physical connectivity, which suggest whether households are able to tap into alternative options for taking advantage of opportunities and accessing the resources needed to deal effectively with shocks, i.e., to adapt (Frankenberger and Nelson 2013).

DFID/TANGO Resilience Conceptual Framework

The disaster resilience framework promoted by DFID (2011) involves four elements that describe resilience: context, disturbance, the capacity to deal with disturbance and reaction to disturbance. This approach considers whose resilience (e.g., individuals, households, communities, national governments), resilience to what (the shock or stress to which the system is exposed), the degree of exposure (large-scale versus differential exposure), sensitivity (ability to cope in the short-term), the ability to adapt – both in anticipation of and in response to – changing conditions over the long term, and how the system responds to the disturbance (e.g., survive, cope, recover, learn, transform) (Brooks et al. 2014).

While DFID's framework approaches resilience primarily from a disaster risk reduction (DRR) perspective, other approaches include climate change adaptation (ACCRA 2012; Oxfam 2011) and improved livelihoods (Alinovi et al. 2010). One of the challenges of a DRR-centric approach is the short funding cycle (often less than two years), which limits the ability of resilience programming to promote and improve adaptive capacity or address the longer-term enabling conditions necessary to remove the structural causes of vulnerability. A longer-term systems approach was needed that combined emergency aid with development programming; an approach that was multi-sectoral and that promoted synergistic partnerships/alliances between NGOs and other actors.

The resilience framework presented by Frankenberger et al. (2012) – and updated here –integrates livelihoods, DRR and climate change adaptation approaches into a single framework for assessing resilience (Figure 6) (Frankenberger et al. 2014). This integrated systems approach emphasizes the importance of absorptive, adaptive and transformative capacities that include access to productive assets, household livelihood strategies, and institutional structures and processes, as well as preparedness, prevention, response and recovery activities formulated to achieve well-being outcomes in response to shocks and climate-related stresses.

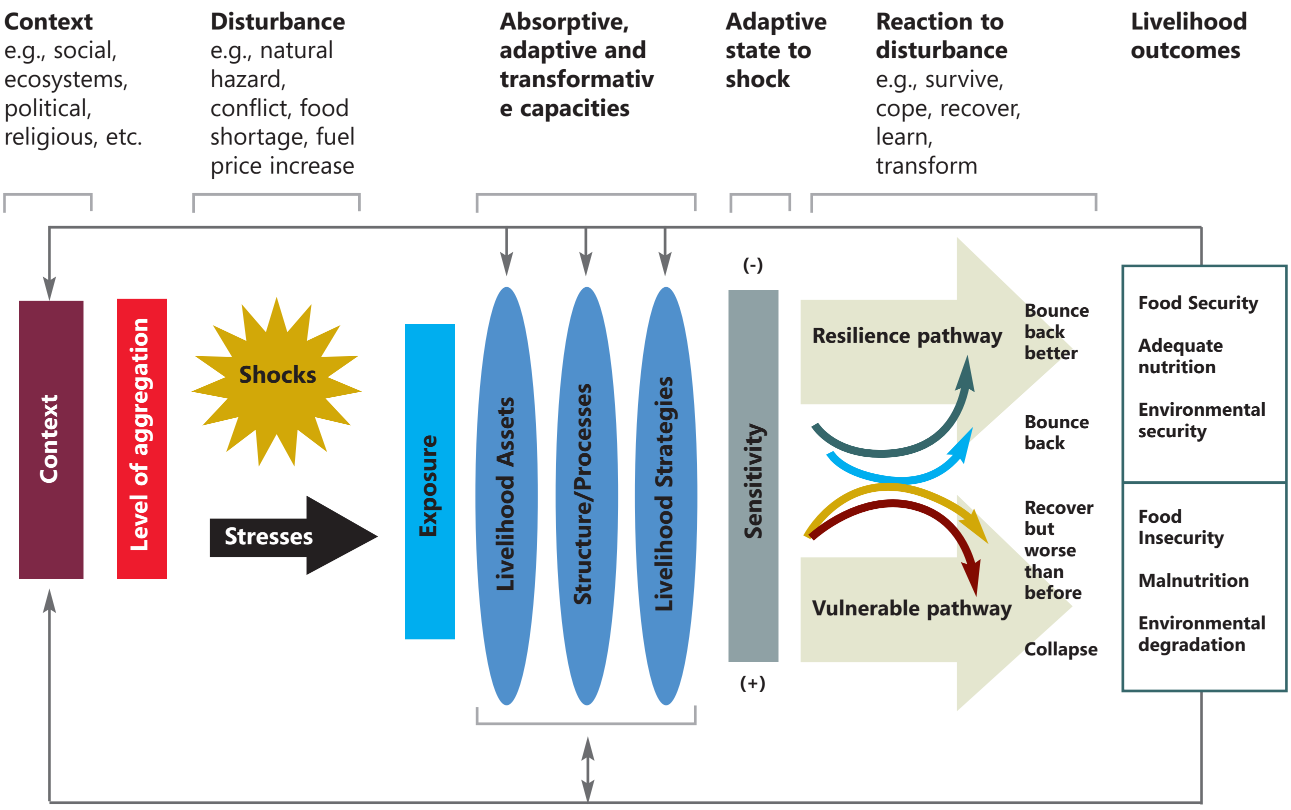
The important variables of interest are composite measures based on several other measures. In many of these cases, Principal Components Analysis (PCA) or polychoric factor analysis is used to construct an index. These techniques reduce a set of 'input' variables that are hypothesized to be related to one another by detecting the structure of the relationships among the input variables from their correlation matrix. PCA can be used when all of the input variables are continuous. Polychoric factor analysis[20] is the PCA analogue that is used when some variables are binary or ordinal. For both, the variables are combined using weights that represent their correlations with the single variable produced.

20. Kolenikov, S. & Angeles, G. (2004), *The use of discrete data in PCA: Theory, simulations, and applications to socioeconomic indices*, Working paper WP-04-85, MEASURE/Evaluation project, Carolina Population Center, University of North Carolina, Chapel Hill.

Indexes are constructed using this technique only if the signs of the weights for the input variables are as expected (positive or negative), given the conceptual understanding of the relationships between the input variables and the indicator being measured.

Note that for all indexes constructed, the first principal component (or equivalent, for polychoric factor analysis) is used to construct the index. This component, which accounts for as much of the variability in the data as possible, always turns out to be the one for which the input variables enter with the appropriate sign – a positive indication of the conceptual validity of the indicators.
Multivariate regression analysis is used to investigate the structural relationships that are hypothesized to exist between the key variables of the analysis (well-being outcomes, shock exposure and resilience capacities) for the population being studied. This approach has been applied in Niger, Somalia and, more recently, Ethiopia.

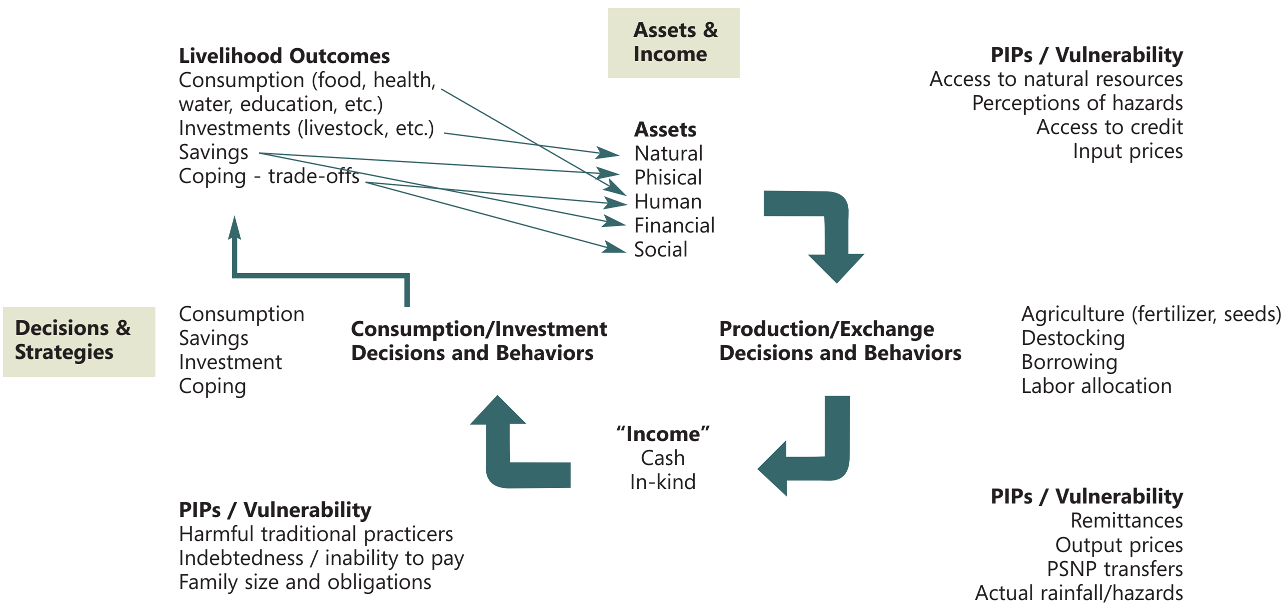
Figure 6. DFID/TANGO Resilience Conceptual Framework



Tufts Livelihoods Change Over Time (LCOT) Model

The Feinstein International Center at Tufts University, in collaboration with World Vision and the College of Dryland Agriculture and Natural Resources at Mekelle University in Tigray, is measuring resilience in Northern Ethiopia by assessing "livelihoods change over time" (LCOT) (Maxwell et al. 2013; Vaitla et al. 2012). The LCOT conceptual model adopted here captures static livelihood outcomes (e.g., food security, health status, education level), which are typically measured in a fairly linear manner, as well as more complex outcomes based on dynamic interactions between livelihood strategies, policies and programmes, and institutions, which can enhance or limit household responses. Based on a livelihoods cycle framework, the LCOT assessment involves first understanding the shocks inherent in the system (i.e., what types of shocks or hazards are occurring within the targeted population), and subsequently how a given shock affects different stages of the livelihoods cycle (i.e., how assets are affected by a particular shock, how production and other decisions are impacted by a shock, and how policies/institutions mitigate the risk of a shock). Such information is then used to identify who is most vulnerable to what types of shocks. Rather than collect the large amount of data required to directly measure various parts of the livelihoods cycle, a model is used to estimate relationships between initial asset levels, variables at different stages of the livelihoods cycle, and outcome measures of household resilience (Maxwell et al. 2013; Vaitla et al. 2012). Figure 7 illustrates the livelihoods cycle framework:

Figure 7. Detailed "livelihoods cycle" framework adapted for Tigray, Ethiopia



Source: Maxwell et al. 2013

To measure resilience, the study utilizes a number of indices, scores and individual variables to look at changes in seven indicators of livelihoods outcomes and household well-being across years (i.e., from hunger season to hunger season): Household Food Insecurity and Access Scale (HFIAS), Coping Strategies Index (CSI), Food Consumption Score (FCS), Illness Score, Value of Productive Assets, Net Debt, and Income (per capita daily expenditure). The HFIAS, CSI and FCS are used to assess food security. An illness score measures human capital. Additional scores (or indices) include access to community resources (i.e., access to community-owned land, pasture/grazing land, water sources, forest resources); support network score (i.e., ability to access non-family networks in case of a shock); social participation score (i.e., household participation in formal and informal groups); and crop diversity index (i.e., cropping system patterns). Asset variables include both those more likely to change in the short term (e.g., value of land, livestock, productive assets) as well as those more likely to change over the long term (e.g., literacy, participation in social organizations).

OXFAM and ACCRA: From characteristic-based approaches to capacity-focused approaches

Thinking on resilience has evolved from a characteristics-based approach to a capacity-focused approach. Promoted by Oxfam GB (Hughes 2012), ACCRA (2012) and others, the 'characteristics based approach' attempts to identify reliable determinants of household and community resilience that can be assessed before shocks occur. It focuses on asset-based approaches, as well as the intangible processes and functions that support adaptive capacity.

The approach developed by Oxfam GB measures resilience based on a number of dimensions that were hypothesized to characterize resilience using the Alkire-Foster index (Brooks et. al. 2014). Measurement is based on characteristics/proxies without consideration of the shock. Oxfam considers five dimensions as key to resilience: livelihood viability, innovation potential, contingency resources and support access, integrity of natural and built environment, and social and institutional capability (Hughes 2012). Though Oxfam views these five dimensions as critical to household resilience, the specific characteristics determining resilience and/or adaptation in a particular context vary widely.

The Africa Climate Change Resilience Alliance (ACCRA) is a consortium of NGOs (Oxfam GB, the Overseas Development Institute [ODI], Save the Children Alliance, CARE International and World Vision International), which developed the Local Adaptive Capacity Framework (LAC) (Frankenberger and Nelson 2013). In the LAC framework, adaptive capacity is broken down into five characteristics: asset base, institutions and entitlements, knowledge and information, innovation and flexible and forward decision-making, and governance.

These characteristic-based approaches are often derived using bottom-up participatory methods (Winderl 2014). Defining a set of resilient characteristics has the advantage of being adapted to different geographical settings, cultures and environments. Identifying a set of characteristics as a proxy for resilience tends to be case-specific and cannot be easily generalized (Winderl 2014).

The most significant weakness of an inductive characteristic-based approach to resilience measurement is the problem of circular logic, whereby resilience is measured using the very same characteristics that are considered the key elements of resilience (Winderl 2014). Another significant limitation to the characteristics-based approach is that it does not address whether the characteristics identified are actually relevant when different shocks occur (Frankenberger and Nelson 2013). As the work of Béné et al. (2012) highlights, resilience is a process rather than a static state, and as such, its determinants are constantly changing as the social, economic and environmental landscapes within which households and communities operate also change.

Although a resilience approach can bridge the gap between humanitarian aid and development activities, it must also provide clear guidance on resilience programming that is different from existing sector-specific approaches (Mitchell 2013). Mitchell (2013) suggests that the added value of a resilience approach combines core programming with risk management approaches that build absorptive, adaptive and transformative capacities. Thus, resilience is not the primary programme objective (i.e., the 'what'), but rather defines how programming is implemented to achieve the primary objective. This is consistent with the resilience framework presented in Figure 2, in that success of the intervention is measured not by 'resilience' *per se* but by achieving certain positive livelihood outcomes (e.g., food security, adequate nutrition).

This underscores another shift in resilience thinking over the last few years: improved resilience capacity is best measured with multiple types of indicators, including those that measure the shock(s) and/or stressors that occur, rather than with single outcome indices. Many existing resilience indices do not take into account different types of shocks and stressors. Guidance from the RM-TWG suggests resilience can be measured as a capacity (absorptive, adaptive and transformative capacities) that enables households and communities to maintain a minimum threshold condition when exposed to shocks and stressors (Constas et al. 2014).

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Resilience has emerged as a framework for enhancing people's and communities' capacities to reduce their exposure, cope with and/or adapt to shocks. However, a common understanding of how to assess and predict resilience levels, and to evaluate the impact of resilience programmes, is lacking. In this context, the *Resilience Measurement Technical Working Group* (RM-TWG) was established under the auspices of the Food Security Information Network (FSIN) to identify and promote means of **operationalizing the concept of resilience** in humanitarian and development practice, primarily through research and technical oversight related to resilience measurement.

Operationalizing resilience measurement will require that practitioners provide credible, data-based insights into the attributes, capacities and processes observed at various scales (e.g., individual, household, community, national) and maximize the use of available data from ongoing resilience initiatives.

Therefore, the RM-TWG promotes the adoption of best practice in resilience measurement through collaborative development of three primary outputs:

- a **paper** on resilience measurement principles and definition of resilience;
- a common **analytical framework** for resilience measurement; and
- **technical guidelines** for resilience measurement.

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