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REPORT 7

Classification of Indicators for Resilience Analysis: An Assessment of Selected Data Sources Focused on Arid and Semi-Arid Lands

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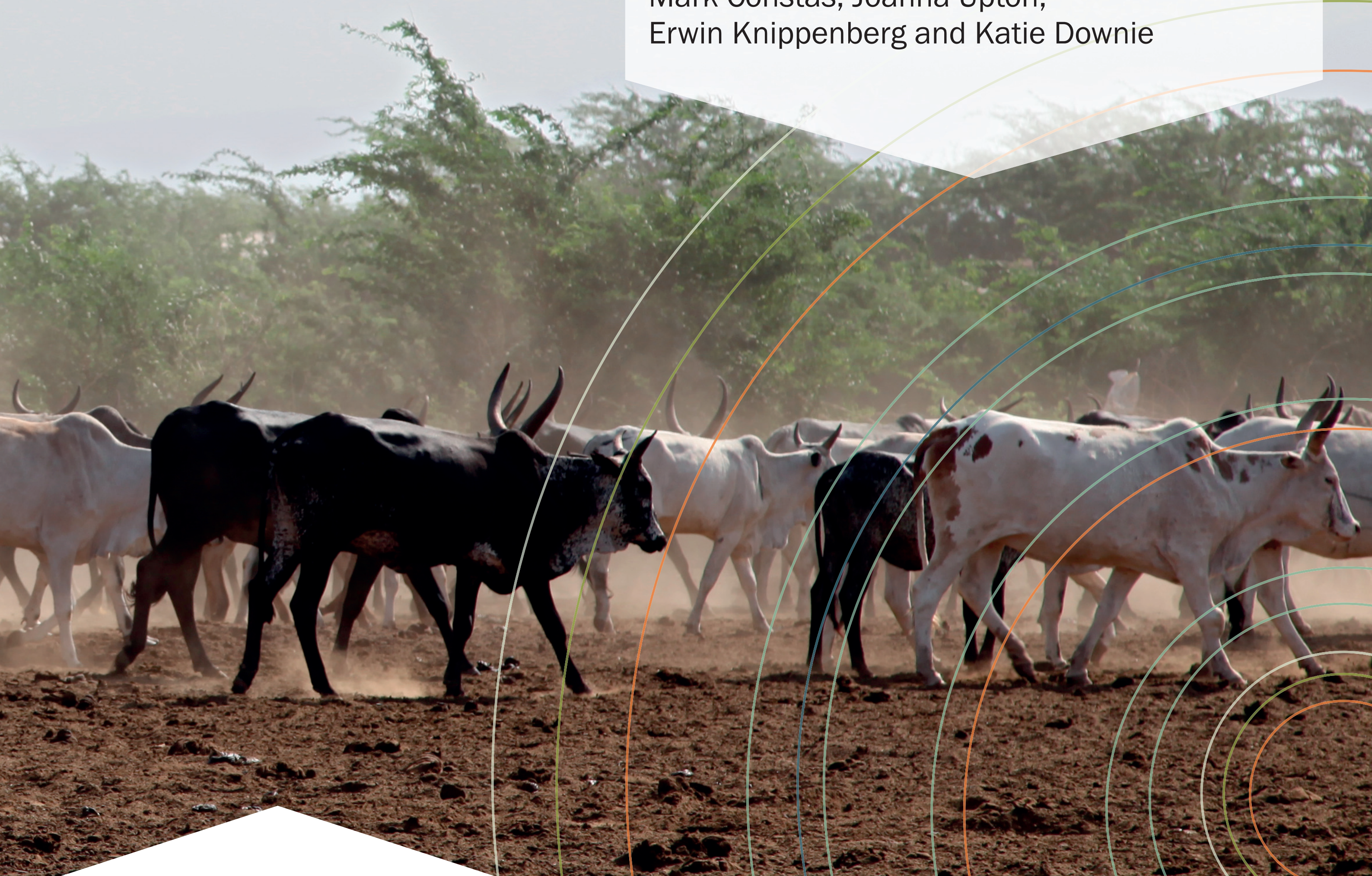

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Introduction and overview

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Over the past few years, there has been a surge of interest in resilience as a core concept on which strategic planning for development assistance and humanitarian aid might be based. Initially introduced as concept to drive policies and programmes, more recent activity has been focused on measurement. Questions raised about resilience measurement are motivated by the need to assess the impacts of the growing number of policies and programs that are meant to promote resilience. From an analytical vantage point, addressing questions about measurement will underwrite efforts to understand and model the dynamics that account for varied outcomes following shock exposure. Why do some households and/communities manage shocks better than others? How can programmes and policies be best targeted to meet the needs of populations that live in shock-prone contexts? Measurement that is well-tailored to such resilience-oriented questions sets the stage for constructing data-based inferences to guide and evaluate investment decisions.

While measurement involves a range of theoretical and technical issues, an early step in the measurement process is focused on the task of selecting the most appropriate indicators for a given measurement topic. In the case of resilience measurement, there exist a need to identify indicators that will enable one to assess the wellbeing of individuals and groups who live in shock prone contexts and determine why some individuals and groups recover better than others. One way to respond to this need is to design primary data collection studies that will support the effort to conduct resilience analysis. While the task of conducting primary data collection on resilience, with tailor-made indicators, has certain benefits, the opportunity to make use of existing datasets also needs to be explored. Cost and capacity constraints often make the task of constructing new data collection tools an impractical option. From an efficiency perspective, it also makes sense to leverage existing data to the fullest extent before launching new, and often costly, data collection efforts. Although datasets are regularly reviewed to assess their suitability for analysis, the typical review focuses on issues such as sample size, number and spacing of data collection events, and missing data. With the substantial investments in resilience programming and policy, there now exists a need to review datasets to assess opportunities for resilience analyses. Recognizing this need, The Technical Consortium for Building Resilience in the Horn of Africa (TC) has established a portfolio of work that responds directly to growing need for empirically-based resilience analyses.

Under the direction of the TC, the *Classification of Indicators for Resilience Analysis* (CIRA) project was undertaken as a proof of concept study in which selected datasets were used to test a resilience-focused review framework. The design and implementation of CIRA was informed by recommendations provided by the Food Security Information Network's (FSIN) Resilience Measurement Technical Working Group (RMTWG) (Constas, Frankenberger & Hoddinott, 2014) and is consistent with the theoretical framework of development resilience (see Barrett & Constas, 2014). On an operational level, the way in which indicators are classified was also directly informed by the causal framework for resilience measurement (Constas et al., 2014). The idea for a review framework focused on resilience is based on resilience sensitivity analysis methodology (see Constas & Frankenberger, 2016), an approach that was developed to guide the review of data collection tools and analytical models[1].

[1] An earlier version of the framework on which CIRA is based was presented as a data architecture model for resilience analysis (see Constas & Downie, 2014).

The specific purpose of the present report is to describe the results produced from the CIRA study. The question that motivated the study concerns the suitability of datasets for resilience analysis: *How can one assess the extent to which a given dataset will serve the goal of conducting empirical studies of resilience?* As a task that involved reviewing the contents of datasets, this question was answered by documenting how an array of indicators within a particular dataset satisfies empirical criteria associated with resilience analysis.

Based on a matrix that specifies the types of indicators and properties of indicators required to study resilience, a review framework was developed. The framework was applied by populating it with three datasets as a proof of concept. The three datasets used in this proof of concept study were 1) the Kenya National Drought Management Authority (NDMA) dataset, 2) Kenya Household Safety Net Program (HSNP) dataset, and 3) the International Livestock Research Institute's (ILRI) Index based Livestock Insurance (IBLI) dataset.

Beyond this first introductory section, the present report is organized into four additional sections. The second section describes the context of the CIRA study. The third section describes the review procedures that were used for the CIRA study. The fourth sections contain descriptions of the results of the review. The report concludes with highlights of some of the challenges of the CIRA study and discusses possible next steps following the proof of concept stage of the study.

The context of CIRA study

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The context of the CIRA study is the Arid and Semi-Arid Lands (ASALs) of Kenya with special reference to recently established policy, the Kenya Ending Drought Emergencies Common Programme Framework (EDE– CPF). The administrative body responsible for the EDE-CPF is the National Drought Management Authority (NDMA) in Kenya. As noted above, the immediate organizational context for the CIRA study is the Technical Consortium (TC), established to help consolidate CGIAR and other research efforts for improvement of the resilience of ASAL populations in the Horn[2]. As part of these efforts, the TC engaged in particular with the National Drought Management Authority (NDMA) in Kenya, an agency which serves as the focal point for planning and implementing the EDE-CPF.

Recent devolution of power in Kenya has shifted more control into the former districts, now counties. These devolved county governments in turn commissioned and/or developed the individual county-level County Integrated Development Plans (CIDPs), which are intended to clearly articulate policy priorities. ASAL counties are to work with the NDMA to harmonize these priorities with the EDE – CPF, around promoting resilience enhancing investment decisions. The TC hence has a role in supporting both the centralized NDMA and county-level actors in their work at implementing these plans, in particular knowledge management.

A core part of this process is the increased demand for evidence-based decision-making for policy and investment decisions. An important piece of this, in turn, naturally involves data sources, and in particular reviewing and informing existing national and regional surveys with a view to understanding—and working to improve—their utility for the EDE and for ASAL development more broadly.

3

Review methodology
Four stage approach

One of the main objectives of the CIRA proof of concept project was to develop and test a replicable approach for reviewing the potential of datasets for resilience analysis. With this objective in mind, implementation of the present CIRA study can be described as involving three distinct stages of work. A summary of activities associated with each stage, along with a focal question, as follows:

Stage I: Review foundations- Review emerging theories and conceptions of resilience measurement to develop the resilience data structure.

> *Focal question:* How might extant policy positions, theories, and emerging guidelines on resilience measurement in particular, provide direction on the characteristics of datasets that should be catalogued?

Stage II: Classification methods - Specify frameworks that will be used to conduct a resilience-focus review of datasets.

> *Focal question:* What are categories and properties of indicators that can be used to guide the review of dataset?

Stage III: Dataset selection - Engage individuals that have responsibility for data related to the ASALS and the EDE-CPF and assess available dataset as candidates for review.

> *Focal question:* What datasets are available for resilience analysis and of these, which are sufficiently well documented?

Stage IV: Classification procedures and structure of results – Catalogue datasets by classifying types and properties of indicators according to the resilience sensitivity analysis methodology and using resilience data architecture as structure for reporting results.

> *Focal question:* What are the characteristics of datasets that enable or impede the effort to model resilience dynamics?

Each stage of activity is designed to produce an outcome. The outcome of Stage I is an overview of relevant theory and guidelines on resilience measurement. The outcome of Stage II is a data summary template that guided the task of cataloguing datasets for a particular topic of interest, resilience in the present case. The outcome of Stage III activity was the selection of datasets for review. The outcome associated with Stage IV is a set of tabular summaries that document resilience-related characteristics of a dataset. Once Stage III results have been generated, one can determine relative potential (within and across datasets) for resilience analysis. Descriptions of activities and results associated with each of four stages of the CIRA methodology are described below.

Stage I: Review foundations: theory, technical guidance and pragmatic synthesis

The methodology for the CIRA study drew on two sources of input; the first being more theoretically-oriented and the second, more technically-focused with more direct implications for resilience measurement. The theoretical foundation for this work was an article of development resilience published the Proceedings of the National Academy of Sciences (see Barrett & Constas, 2014). The other more practically focused work that informed CIRA methodology are the set of papers produced by the RMTWG[2] (Constas et al., 2014; Constas, Frankenberger & Hoddinot, 2014). Elements of these inputs were synthesized to generate the output from stage one, the template for classifying datasets.

[2] All outputs from the FSIN Resilience Measurement Technical Working Group can be found here: http://www.fsincop.net/topics/resilience-measurement/outupts/en/

Theoretical background

The concept of resilience has its roots in ecology (among other literatures), and is referred to primarily with respect to the capacity of a system to respond to disturbance by resisting damage and recovering quickly (Holling, 1973). While fairly new in the area of human systems and development in particular, the appeal of the concept derived not only from the importance of a focus on "systems," but also its links to vulnerability, and the notion of attention to shocks and shock response, particularly in light of the rising importance of climate change and related risks. It was also seen as a way of reconciling humanitarian or emergency programming with the longer-term focus of development and/or livelihoods-based approaches, a common and long-standing aspiration for many practitioners.

Given its strong appeal and applicability in many contexts, the popularity of the concept in development circles quickly out-paced the analytical rigor with which it was approached. To address this widening gap, Barrett and Constas developed a theory of resilience for international development applications (see Barrett & Constas 2014). Drawing from fields of ecology, economics, and climate and environmental systems, the authors define "development resilience" as "the capacity over time of a person, household or other aggregate unit to avoid poverty in the face of various stressors and in the wake of myriad shocks" (p. 2). The focus is on human wellbeing, which is dynamic, stochastic, and non-linear at the individual level but can also be aggregated into higher-levels at household, community, or other units of social organization. Such wellbeing is also underpinned by the natural resource base; there is an inter-relationship between socioeconomic and ecological variables and this coupled dynamic system is empirically not well understood. The authors assert that such a definition of "development resilience" also conceptually allows for the sought-after reconciliation of development and humanitarian ambitions. With this in mind, the authors define "humanitarian resilience" as the "capacity over time of a person, household, or other aggregate unit to survive in the face of various stressors and in the wake of myriad shocks" (p. 3). With such a definition, "humanitarian resilience" is nestled within "development resilience."

Technical guidance on resilience measurement

The FSIN, which was established in October of 2012 under the joint leadership of the Food and Agriculture Organization (FAO), the World Food Programme (WFP) and the International Food Policy Research Institute (IFPRI), responded to the proliferation of ideas and methods around resilience by organizing *The Expert Consultation on Resilience Measurement.* The Expert Consultation brought together a group of approximately 50 individuals from various academic, UN, and non-profit organizations in February of 2013 to assess the state of resilience meaning and measurement, and develop best practices. One of the outcomes of this meeting was a decision to form The Resilience Measurement Technical Working Group (RMTWG). The RMTWG has to date produced two documents on resilience measurement. The first paper (referred to here as Paper 1) was published in early 2014 (see Constas et al. 2014a). The second, referred to as Paper 2, was published in November of 2014 (see Constas, Frankenberger & Hoddinott, 2014).

To create the conditions for sound measurement of resilience, the RMTWG papers set out five questions that need to be satisfactorily answered:

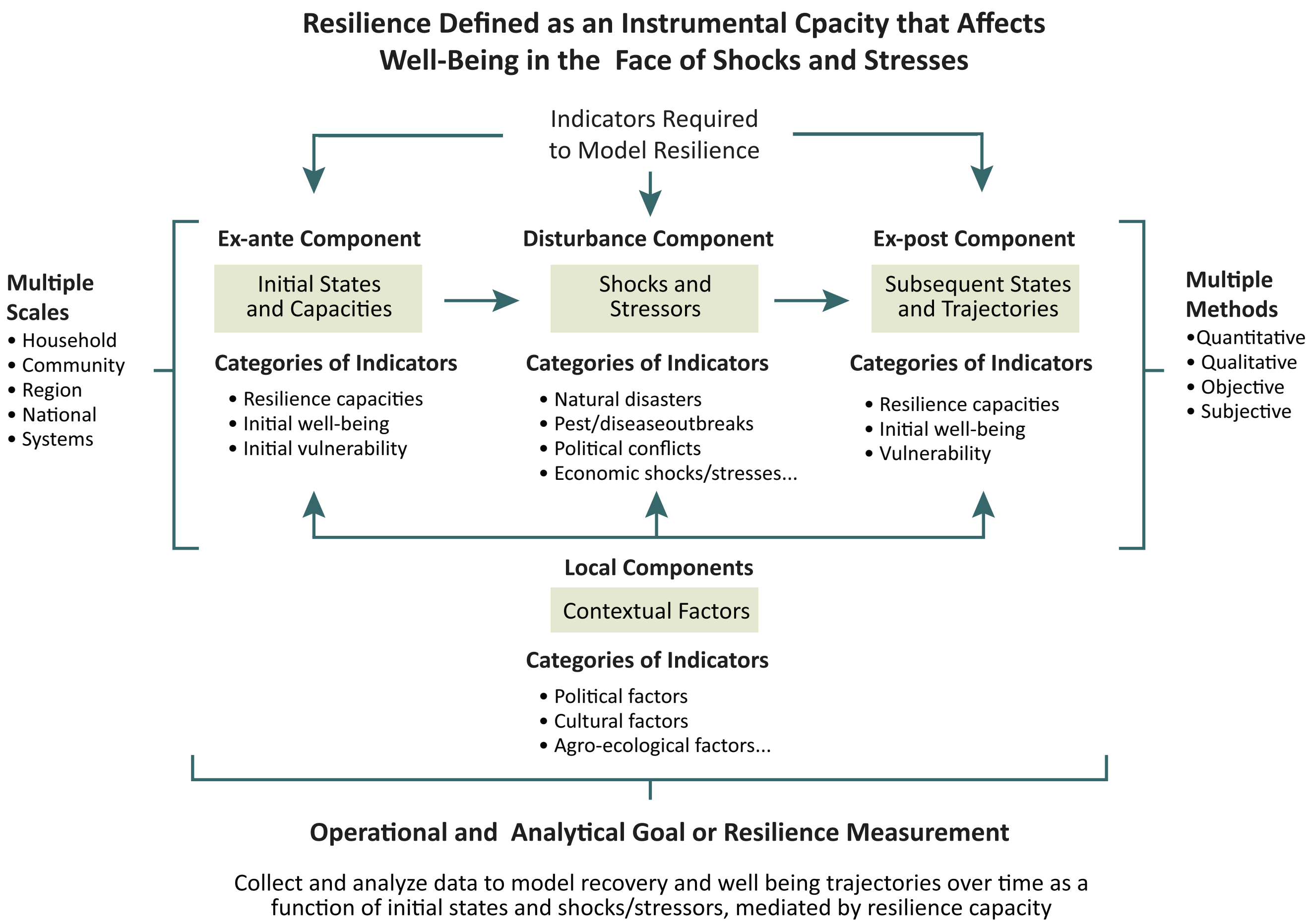
1. **Definition** – How should resilience be defined on a conceptual level?
2. **Simple function** – How is resilience defined within a simple functional relationship that illustrates the way in which the measurement of resilience can help one predict wellbeing in the face of shocks?
3. **Construct specification** – What are the key features of the resilience construct that one should be sensitive to in the process of developing measurement tools?
4. **Methodologies** – What is the range of methodological issues that one should consider to ensure that measures are technically sound?
5. **Causal model** – How is resilience located within a causal chain of events (or conditions) that affect wellbeing and how is it represented in terms of an estimation model?

To answer the first question, Paper 1 defines resilience as "the capacity that ensures adverse stressors and shocks do not have long-lasting adverse development consequences" (Constas et al. 2014a, p. 6).

There are two important features of the RMTWG's definition of resilience, both of which have implications for measurement. First, resilience is defined as a capacity, and second as predictor variable. Resilience is thus included along with other variables (e.g., shocks, vulnerability) that are important for predicting future states of wellbeing (e.g., food security, health, economic security etc.).

The second paper produced by the RMTWG moves beyond the discussion of resilience measurement as a conceptual issue and toward an analytical model that would help frame resilience as the focus of empirical work. The common analytical model, which offered a causal model that was presented in Paper No. 2, is shown below:

Figure 1. Causal Framework for Resilience Measurement



From the perspective of specifying and classifying indicators, the common analytical model highlights the idea that resilience is best measured as a time-dependent phenomenon that examines the relationship among initial state of wellbeing, disturbances (objectively observed and experienced), and subsequent state of wellbeing. Measures should be taken at multiple scales using multiple methods. Resilience capacities exert their influence both before and after shocks and measures of such capacities should be tracked over time. Key contextual factors should be identified and measured. The dimension of time is critical and it is important to measure the impact of resilience-focused interventions with frequent measures and over extended periods of time.

Stage II: Synthesis and development of review frameworks

The review of recent theoretical and technical work on resilience measurement suggests that data intended for resilience analysis may be organized according to basic dimensions, the integration of which highlights the kind of indicators needed for resilience analysis.

- **Focus of indicators** – specifies the content of indicators required for resilience measurement and analysis.
- **Properties of indicators** – specifies methodological characteristics and the temporal characteristics that data should possesses for resilience analysis.

The focus of indicators and properties of indicators represent two dimensions that, together, define the empirical requirements for resilience analysis. Stated as a question, the focus of indicators question asks “what needs to be measured?” This first question draws attention to the basic empirical requirement of resilience. The dimension involving the properties of indicators requires two questions. The first question asks “what tools (e.g., qualitative and quantitative) and perspectives (e.g., objective, subjective) should be used to collect data?’ This is essentially a methodological question. The second question draws attention to the temporal properties of indicators – “at what points and at what scale shall data be collected?”

Each of the two dimensions that guided CIRA process is described very briefly below. A final section provides a framework that illustrates how the two dimensions are integrated to form a coherent data architecture for resilience measurement.

Focus of indicators. Consistent with the emerging literature on resilience (e.g., Barrett and Constas, 2014; Constas et al., 2014a, 2014b; Frankenberger, et al., 2014), five sets of indicators are required for the empirical study of resilience. Table 1 provides a list of the categories of indicators needed for resilience analysis. A description and a sample of indicators associated with each category are provided.

Table 1. Focus Indicators Required for Resilience Analysis

CATEGORIES OF INDICATORS FOR RESILIENCE MEASUREMENT	
INDICATOR CATEGORY	**DESCRIPTION OF FOCUS OF INDICATORS**
Wellbeing Outcomes Quality of life variables	Indicators that provide measures of conditions related to food security, health (physical and mental), poverty, and personal security
Shocks and Stressors Risk exposure variables	Indicators that provide measures of events and conditions that are seen as threatening one or more wellbeing outcomes
Resilience Capacities Social and economic variables	Indicators that provide measures of the set of characteristics (e.g., economic and material assets, human capital, social capital) and abilities (e.g., risk mitigation, buffering, etc.) possessed by some unit (e.g., household and communities) that are viewed as enhancing the ability to absorb, adapt, or transform in the face of a shock and/stressor.
Household Characteristics Composition and	Indicators that provide measures on the composition (e.g., family size, dependency ratios), household structure (e.g., head of household).
Contextual Factors Enabling characteristics	Indicators that measure situational factors (e.g., agro-ecological conditions, infrastructure, institutions and governance) that affect risk exposure and recovery pathways

As shown in Table 1, resilience analysis requires a minimum of five categories of indicators. For the purposes of classifying indicators from selected datasets and for the purpose of developing replicable procedures, the classification scheme is deliberately general. This allows for flexibility. The specific indicators that may be organized under a given category may vary depending on the purpose resilience analysis. Indicators focused on wellbeing outcomes, for example, might include indicators from food security measures, poverty measures, or physical/mental health measures. The objective in creating a data structure for CIRA was to construct a tool that is both focused and flexible.

Properties of indicators

Methodological properties. Following methodological guidance on resilience measurement (see Constas et al, 2014b; Jones and Tanner, 2015; Maxwell et al, 2015), data on resilience can and should take several different forms. Consistent with recommendations for work in development (see Schaffer, 2013), both quantitative and qualitative data are important for resilience analysis. While quantitative data support the effort to model resilience, qualitative date provide detailed descriptions of the contexts to which such model might be applied.

Table 2 provides a summary of properties of indicators and brief descriptions for each property.

Table 2. Properties of Indicators: Methodological and Temporal Properties

PROPERTIES OF INDICATORS FOR RESILIENCE MEASUREMENT	
METHODOLOGICAL PROPERTIES	
Quantitative Numerical expressions	Indicators constructed from quantitative categories (e.g., asset levels, consumption scores, food security measures) and scaled responses (e.g., Likert scales) or ranking metrics
Qualitative Textual expressions	Indicators constructed from and presented as narratively-based interviews, focus groups, and/or observational methods
Objective Events and conditions	Indicators constructed from reports of events and conditions that can be derived from and/or consistently corroborated by fact-based inputs (e.g., rainfall, drought conditions, price fluctuations)
Subjective Perceptions and projections	Indicators constructed from individual perspectives related to present and future wellbeing states, shocks, and stressors, and ability to absorb, adapt, and transform in the face of shocks.
TEMPORAL-SPATIAL PROPERTIES	
Frequency	Indicators collected at a high enough frequency to observe and model rate of change and fluctuations
Duration	Indicators collected over a period time commensurate with expected rate of change for outcome and explanatory variables of interest
Level of measurement	Indicators measured at multiple levels, thereby enabling multi-level analysis to understand spatial relationships (e.g., HHs, within villages, within communities, within districts, with agro-ecological zones….)

Integrated framework: Focus of indicators X properties of indicators

While not used to classify indicators, the integration of focus of indicators and properties of indicators displays how the two dimensions the constituted CIRA approach intersect with one another. Table 3 provides an illustration of this intersection, offered here as way to synthesize key elements of resilience analysis. The integrated framework could serve as useful heuristic device, one that might be used to diagnose the relative strengths and limitations of a given dataset.

Table 3. Integration Framework of Resilience Review Criteria

INTEGRATION OF REVIEW CRITERIA FOR RESILIENCE INDICATORS			
FOCUS OF INDICATORS	PROPERTIES OF INDICATORS		
	Methodological Properties Qualitative & Quantitative	**Temporal Properties** Frequency & Duration	**Spatial Properties** Scale/Structure
Wellbeing Indicators			
Shocks & Stressor Indicators			
Resilience Capacities			
Context/Enabling Conditions			

Stage III: Datasets selected for review

The first criterion for selecting dataset was geographic focus. Given the mission of the TC, a decision was made to select only those datasets that were focused on the Horn of Africa. Two additional pragmatic criteria for selecting datasets were accessibility and documentation. In consultation with individuals who had responsibility for managing datasets and granting access, three datasets were selected: NDMA monthly assessment data, the HSNP data from Turkana County, and the IBLI panel from Marsabit. While all three datasets are concerned with Kenya, they differ in terms of practical function, period of data collection, data availability, and sample size. The basic characteristics of the three datasets are summarized in Table 4.

Table 4. Datasets Selected for Review

DATASET	INTENDED FUNCTION	PERIOD OF DATA COLLECTION	DATA AVAILABILITY	SAMPLE SIZE
NDMA	Early warning	1980 to present	2005 – 2012	630 HHs, 63 villages,
HSNP	Evaluation of HSNP	2012-2014	baseline, 2012	13,860 HHs, 2700 villages,
IBLI	Evaluation of index-insurance	2009-2013	2009-2012	924 HHs, 16 villages

The details of the three datasets reported in Table 4 are general. This information was, however, important for the selection process and could be useful for general planning. More specific details of datasets with respect to resilience are provided below.

Stage IV: Classification procedures and structure of results

The review procedures followed the structure of data templates shown in Tables one and two. The process of classifying indicators began by locating each indicator, for each selected dataset, within a review category. Each dataset was reviewed by at least two team members and meetings were held to settle coding differences. Frequency counts of indicators were used to describe relative strength of a given dataset with reference to resilience.

Results: Focus and properties of indicators across three datasets

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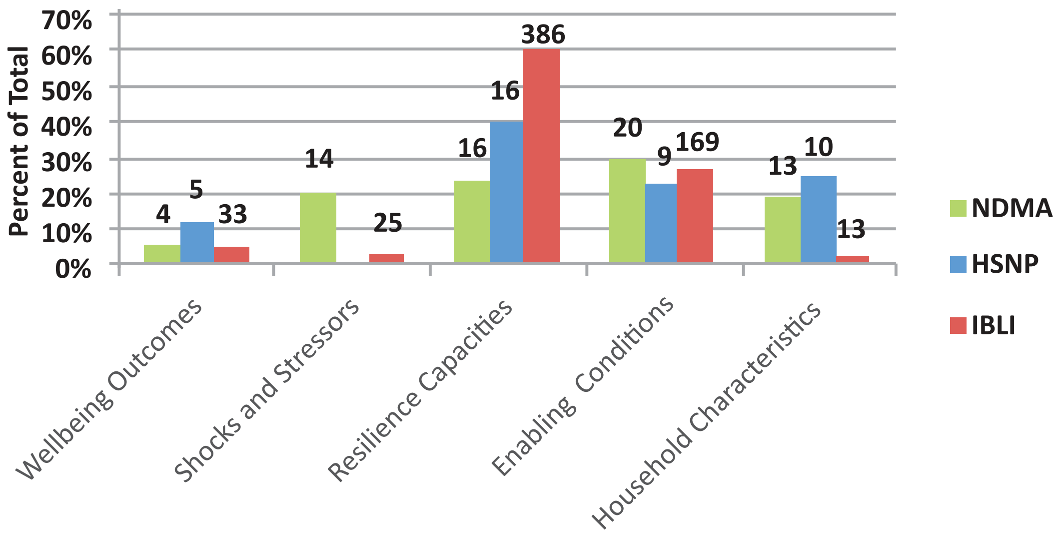
As noted earlier, one of the main objectives of the CIRA study was to summarize the features of selected datasets by describing the extent to which a given dataset satisfied empirical criteria associated with resilience analysis. A second objective was to provide a resilience-focused review of datasets as part of a proof of concept study. The present section describes the results associated with the summary of datasets task.

Results for the review of datasets are presented in three steps. The first step shows the prevalence of indicators for the focus areas. Though not specifically related to resilience analysis, the prevalence of indicators on enabling conditions and household characteristic are also presented. The second step describes sub-categories of resilience-specific indicators (i.e., wellbeing, shocks and stressors, and resilience capacities) and the third step provides a summary of the properties of indicators (i.e., methodological properties and temporal properties).

Overview of focus of indicators

The classification of indicators within and across datasets was designed to document the relative prevalence and specific content of indicators that would be required to conduct resilience analysis. The presentation of findings in the present section first provides an overall picture of the extent to which each dataset contained indicators on the basic set of resilience-focused indicators – wellbeing, shocks and stressors, resilience capacities, enabling conditions, and household characteristics. The relative prevalence of indicators found within each category of indicators, across three datasets reviewed, is shown in Figure 2.

Figure 2. Focus of Indicators in Reviewed Datasets



Moving from left to write on the figure, the first notable finding is that wellbeing indicators represent a relatively small proportion of the indicators. Consistent with its goal of impact assessment, however, HSNP had a slightly higher proportion of its indicators dedicated to wellbeing outcomes.

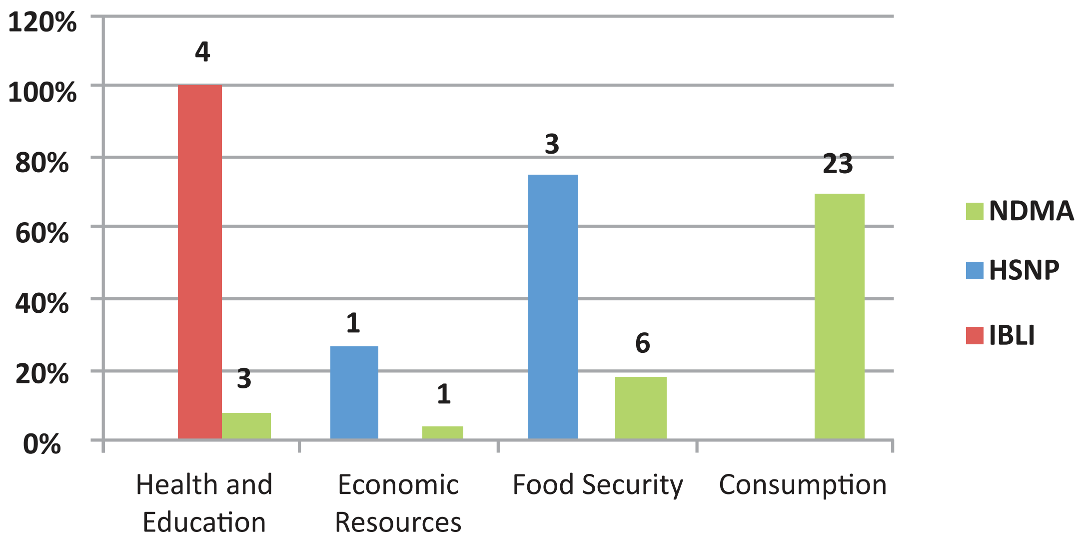
[3] HSNP does collect information on shocks through remote sensing even though it does not include a shock indicator in the survey instrument.

Shocks and stressors, which are a second core element of resilience measurement, are given an uneven amount of attention across the three datasets; HSNP has no indicators that focus on shocks and/or stressors[3]. Figure 2 also shows that, compared to NDMA, HSNP and IBLI datasets dedicate more empirical attention to resilience capacities. Consistent with its early warning goals, the NDMA monthly assessment data dedicates more attention to shocks and stressors. All three datasets dedicate about the same amount of attention to context (i.e., enabling conditions) and household characteristics.

Further analysis of wellbeing indicators

Further classification of indicators categorized as wellbeing indicators was performed. The classification of wellbeing indicators revealed four sub-categories of indicators: 1. health and education, 2. economic resources, such as assets holdings, 3. food security, as measured by the reduced coping strategy index and 4. consumption, a measure of wellbeing commonly used by economists. Figure 3 shows the relative prevalence across these four categories. Prevalence expressed as percentage of total of indicators within the wellbeing category of indicators and the number at the top of a given bar indicates the actual number of associated indicators.

Figure 3. Further Classification of Wellbeing Outcomes



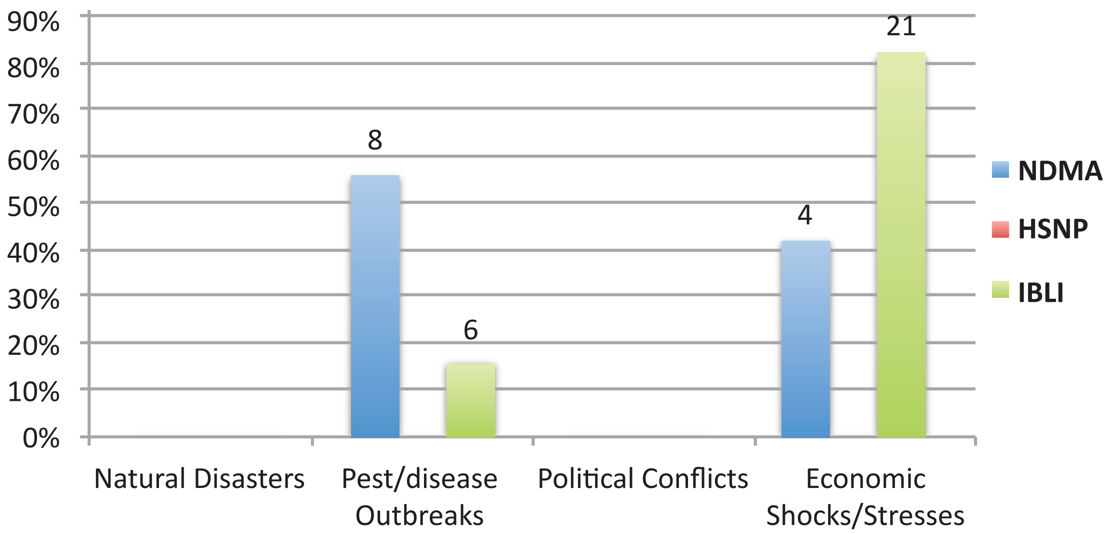
For HSNP, the sub-category of health and education contained all the indicators for wellbeing outcomes that it measured. IBLI also contained the same number of indicators for health and education. On a percentage basis, however, the four indicators for health and education represented less than 10 % of the total number of indicators under the wellbeing category. This was because IBLI allocated about 77 % (23 indicators) of its wellbeing indicators to consumption. The next highest number of wellbeing indicators for IBLI was for food security, which amounted to roughly 19 % of its total wellbeing indicators. NDMA had four out of its five indicators for wellbeing located under food security.

Further analysis of shocks and stressor indicators

Further classification of indicators categorized as shocks and stressor indicators was performed. The classification of wellbeing indicators revealed that only two sub-categories of indicators were used to provide more specific indicators. 1. disasters, such as droughts, floods, and earthquakes, 2. pests and diseases that might affect humans, crops, and livestock, 3. political conflict, such as acts of violence and/protracted disruption of governance that may follow conflict and 4. economic shocks and stressors, such as price shocks, market disruptions, and loss of assets due to theft or other conditions that are not a function of natural disasters and/or pest/disease outbreaks.

Figure 4 shows the relative distribution of these indicators across the datasets sets reviewed.

Figure 4. Further Classification of Shocks and Stressors



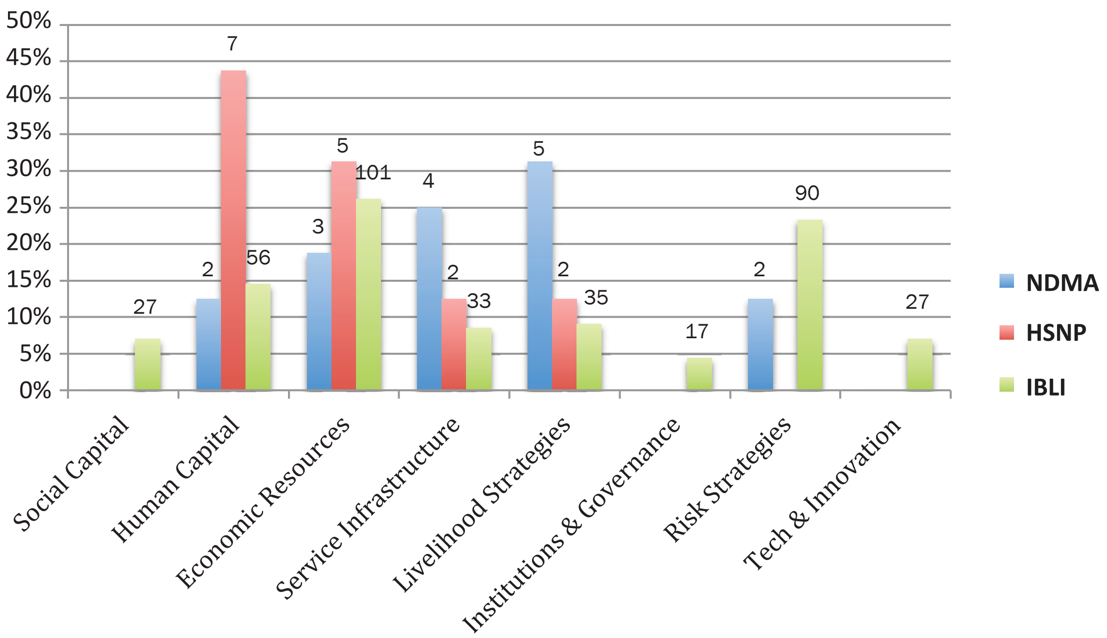
What is immediately noticeable when viewing the results of the further classification of shocks and stressors is the absence of indicators for natural disasters and political conflict. IBLI had the highest absolute number of indicators for shocks and stressors, with 27 indicators, the majority of which (21 indicators or 78 %) were allocated to economic shocks and stressors.

Further analysis of resilience capacities

Further classification of indicators categorized as resilience capacity indicators revealed eight subcategories. A broad definition of capacities was deliberately used, primarily because an ex ante definition of resilience is hypothetical. Eight subcategories of indicators that could plausibly help a household absorb, adapt to, or transform in the face of shocks and stressors were included as a resilience capacity sub-category: 1. social capital, connections and group membership, and access to revenue through mechanisms such as remittances and borrowing, 2. human capital, such as education, 3.economic resources, 4, service infrastructure, 5. livelihood strategies (number of distinct, but not coded by risk), 6. institutions and governance, 7.risk strategies and 8. technology and innovation.

Figure 5 shows the relative distribution of these indicators across the datasets reviewed. As a raw count of indictors, IBLI stands out as providing the largest number of resilience capacity indicators. Between the two subcategories of economic resources and risk strategies, IBLI had nearly 200 indicators that could be used for analyzing resilience capacities.

Figure 5. Further Classification of Resilience Capacities



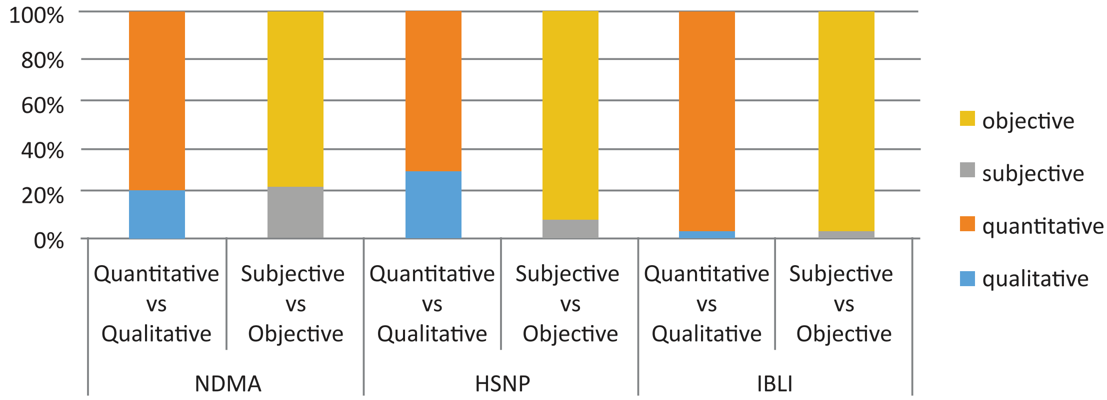
Properties of indicators

Results from the properties of indicators review showed the methodological and temporal features of the datasets that were reviewed. The review of methodological properties documents the extent to which each dataset included subjective indicators and qualitative data. Figure 6 shows the results of the methodological properties of the datasets.

IBLI was the most uniform of the datasets and relied almost exclusively on quantitative and objective indictors.

HSNP was slightly more balanced with reference to qualitative methods but still relied most strongly on quantitative indicators. Of the three datasets, NDMA was perhaps the most balanced. When reviewing the overall findings presented in Figure 6, it is apparent that the selection of indicators reviewed across the three datasets reflected an interest in collecting data using objective and qualitative data.

Figure 6. Methodological Properties

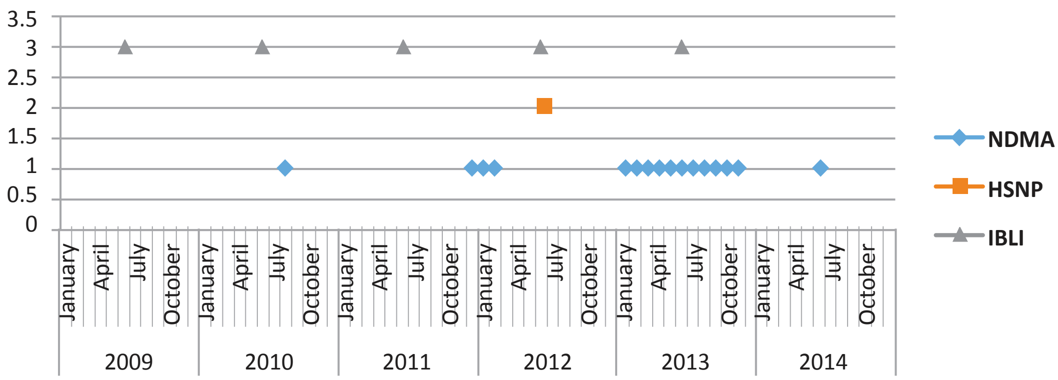


As we can see, the datasets are overwhelmingly quantitative not qualitative, though the NDMA has a higher portion of both compared with IBLI, as you would expect in an 'early warning' dataset. HSNP seems to split the difference, seeking to measure a number of qualitative indicators, notably related to the underlying motivations of observed decisions, i.e.,"why didn't you go to school?". HSNP does make an effort to minimize subjective questions.

Temporal properties

Figure 7 shows the duration and frequency of data collection for each of the three datasets.

Figure 7. Temporal Properties of Indicators



The review of temporal properties showed that the IBLI dataset had the most consistent data collection (annually) over the longest period of time. While administered less regularly, NDMA is the dataset with indicators collected on a monthly basis. Consistent with the objectives of early warning dataset, data for the NDMA are collected with relatively high frequency. Given the large gaps in data availability, the review of the dataset suggests an inconsistent reporting mechanism. Efforts to systematically collect and centralize these field reports would greatly enhance the NDMA's potential for analysis. The dataset is particularly suited for short-term shocks. The HSNP has only collected one round of surveys, though two more panels are planned for the future (specific dates are not known at the writing of the present report). IBLI's annual rounds, tracking households over time, allows one to discern long term trends, including shocks and post-shock response trajectories, which facilitate attempts to measure resilience.

Conclusions

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Measuring resilience is about measuring changes in wellbeing status, over appropriate periods of time, in the face of (and following) shocks and stressors. To gain data-based insights about resilience, indicators focused on wellbeing and shocks are therefore essential. In a sense, these two sets of indicators represent a minimum set of indicators for resilience analysis. If, however, one aims to explain why some households and communities fare better over time, additional indicators are required. Technical guidelines (Constas, Frankenberger & Hoddinott, 2014; Constas et al., 2014), theoretical notions, and emerging empirical work (Smith et al., 2015), suggest that indicators related to resilience capacities and contexts can help explain variations in wellbeing over time. To support efforts to leverage existing datasets for resilience analysis the present report developed and applied a resilience-focused review methodology, *Classification of Indicators for Resilience Analysis* (CIRA).

Conceptualized as a proof of concept, the results of the CIRA study revealed strengths and limitations in a sample of three datasets that were selected for review. Perhaps, more importantly, the CIRA project demonstrated how a resilience-focused review of datasets could be conceptualized and performed. Conceived as a generalizable resilience-focused protocol for reviewing datasets, CIRA represents a first step in much needed set of data-mining activities that may have the capacity to underwrite resilience analysis.

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