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Resilient, but from whose perspective? Like-for-like comparison of objective and subjective evaluations of resilience

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Abstract

Resilience has quickly risen to prominence amongst the international development community. Donors, governments and civil society organisations are making ever-larger political and financial commitments towards supporting resilience in the face of changing global risks. Accurate measurement of resilience is thus crucial in ensuring that resilience-building activities are effective and target communities most in need. To date, resilience measurement is heavily reliant on objective tools and approaches. These refer to measurement practices that are independent of the judgement and perspectives of those being evaluated (either with regards to how resilience is defined or evaluated). More recently, scholars and practitioners proposed a range of subjective approaches. They follow a contrasting approach – seeking to factor people's own judgements and evaluations directly into the measurement process. More specifically, they make use of people's perceptions of what resilience means to them and rely on self-evaluations of their own capacity to deal with risk. While both approaches have their strength and weaknesses, little is known about how objective and subjective modes of evaluation compare.

This paper addresses these questions, focusing on measurements of household resilience to a range of risks. To do so we introduce a new method of subjective-evaluation termed the Subjective self-Evaluated Resilience Score (SERS). Using a regionally representative household survey of 2308 households in Northern Uganda, we assigned a range of SERS modules, alongside a traditional objective module of resilience measurement. This allowed like-for-like comparisons of the objective- and subjectively evaluated resilience scores for the first time. Findings from the survey suggest there is a moderate relationship between objective and subjective modules, with SERS scores demonstrating similar positive influences on the main components of objectively-evaluated resilience. While both modules share many of the same underlying factors, there are notable differences, particularly with regards to associations with coping strategies, levels of education and exposure to prior shocks. We also investigate different ways of characterising subjectively-evaluated resilience and find few areas of divergence. Findings highlight the need for existing measurement toolkits to pay closer attention to the selection of pre-existing indicators and offer opportunities for combining subjective and objective methods of evaluating resilience.

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1. Introduction

Research measurement is big business. As political momentum in support of resilience-building interventions gathers, a plethora of toolkits for measuring resilience have sprouted in recent years (Shipper and Langston 2015; Bahadur & Pichon 2017). To date, the vast majority of these tookits rely on objective forms of measurement (Jones and Tanner 2017). Broadly speaking, these can be described as approaches that are independent of judgement and perceptions of the individual (or system) being observed. Here objectivity can relate to two aspects: how resilience is *defined* (i.e. who decides what resilience is and the characteristics that make a system resilient?); and how it is *evaluated* (i.e. is resilience is measured via external observation or self-evaluated judgements?) (see Jones 2018).

Objective tools have many advantages, including: fixed and transparent characterisations of resilience; options for standardisation across groups; and the relatively ease in which tangible indicators can be measured. Yet they are not without their weaknesses (Levine 2014). For one, agreeing on a common set of observable indicators that constitute resilience has thus far proven a considerable challenge; this is despite growing consensus amongst the resilience measurement community around indicator selection and transparency (FSIN 2014). One reason is due to the fact that resilience is made up of a multitude of intangible processes – such as community cohesion or social capital - that are difficult to capture using objective forms of measurement (Adger 1999). Moreover, resilience is largely context dependent and varies across geographic and temporal scales. At the household level, measurement frameworks revolve heavily on large sets of proxy indicators, requiring significant amounts of socioeconomic data to be collected.

Most importantly, objective approaches do not currently take into account the wealth of knowledge that people have of their own resilience and the contextual information that can help inform it. This includes important internal factors such as mental states, aspirations and psychological resilience which are fundamental in shaping an individual - and the household that contains them - reaction to external shock (Cox and Perry 2011; Maxwell et al. 2015).

It is for this reason that alternative methods of resilience measurement have been sought in recent years. One promising approach is offered in the form of subjective tools of assessment (Maxwell et al. 2015; Jones and Tanner 2017; Jones and Samman 2016; Claire et al 2017; Marshall 2010; Seara et al. 2016; Nguyen and James 2013; Béné et al. 2016a; Sutton and Tobin 2012). Subjective approaches start from the premise that people have a legitimate understanding of the risks that they face. As with the case of objective tools, subjective approaches can relate to both how resilience is defined and evaluated. They are therefore associated with modes of measurement that depend on people's judgement of what constitutes resilience and self-evaluations of their own capacity to deal with risk.

Subjective tools have been trialled in a number of different contexts (Jones and Samman 2016; Marshall 2010; Seara et al. 2016; Nguyen and James 2013; Béné et al. 2016a), and may provide a useful complement to objective forms of resilience measurement (Maxwell et al. 2015; Clare et al. 2017). Yet, in practice, little empirical evidence exists examining the direct relationship between objective and subjective approaches. Moreover, it is not known how different forms of subjective assessment compare. In this paper, we seek insights into these queries using like-for-like assessments of subjective and objective modules assigned in a regionally-representative survey of 2308 households in Northern Uganda. We introduce a new approach to subjective evaluations of resilience termed the Subjective self-Evaluated Resilience Score (SERS). SERS allows respondents to evaluate their household in relation to a series of resilience-related capacities. Drawing on household-level information on socio-economic of conditions we compare associations between the underlying drivers of subjective and objectively-evaluated resilience. We also examine whether different characterisations of resilience – both in relation to resilience-capacities and hazard-specificity – produce similar outcomes. Finally, we explore the implications of the various comparisons for improving resilience measurement and discuss avenues for further methodological testing and refinement.

2. Background and context

The notion of resilience has a long history spanning multiple academic disciplines (Alexander 2013). In recent decades, the term has gained widespread prominence across the sustainability sciences in describing the perturbation of socio-ecological systems. This rise in popularity has coincided with the adoption of resilience as a unifying framework for guiding international humanitarian and development priorities. Indeed, resilience is now central to a number of international policy commitments, including the UN's Agenda 2030, Sendai Framework for Disaster Risk Reduction and Paris Agreement on climate change (United Nations 2015a,b). While its prevalence has helped to raise awareness of resilience and the importance of ensuring that societies are able to respond to risk, it led to considerable debate and confusion around the term's actually meaning.

Historic applications of resilience, stemming from engineering and ecology, have long been associated with the ability of a given system to return to a normalised state after disturbance or change (Holling 1973; Walker et al. 1981). This clearly has many parallels when translated into understanding social systems. However, social scientists quickly highlighted the importance of adaptation and transformation in thinking through societal responses to change and disturbance. In many ways, these can be seen as somewhat at odds with notions of resilience as bouncing-back, and contributed to considerable conceptual opacity (Olsson et al 2015). As a result, multiple conceptual and evaluative frameworks currently exist, each depicting resilience as made-up of a combination of differing sets of core characteristics (Shipper & Langston 2015; Bahadur & Pichon 2017).

With the above in mind, we choose to apply a narrow definition and application of resilience in order to allow for ease of comparability across resilience modules. Specifically, we focus on a particular unit of analysis: the household. This is due to the centrality of the household unit in dictating responses to external stimuli both at the individual and family and community levels (Toole et al. 2016). Indeed, many of the assets, capabilities and functions commonly assumed to support resilience in social systems derive from, and are dictated by, household-level dynamics (Frankenberger & McCaston 1998). Moreover, taking the household as the primarily unit of analysis allows for interactions between individual and collective decision making processes to be taken into account. It also allows for the influence of wider traits such as social norms, behaviours and institutions that mediate responses to climatic stimuli to be factored in. Importantly, a focus at the household level permits a distinction to be drawn between psychological resilience– associated with the ability of an individual's psyche to deal with shock or trauma – and resilience of the individual and/or household that encapsulate a broader and more holistic system: a point of clarity that is particularly important when assigning modules on subjectively-evaluated resilience (Windle et al. 2011).

Another important distinction relates to the relationship between objectivity and subjectivity. For the purposes of this paper we make use of the objectivity-subjectivity continuum proposed by Jones (2018). The continuum refers to objectivity and subjectivity in resilience measurement according to two key tenants. The first is how resilience is defined. Objective definitions of resilience can be classed as those that are externally derived. In practice, this means that resilience is not determined by the people or system being assessed. Rather, the characteristics (or indicators) used to evaluate resilience are drawn from the wider academic literature or through use of extensive expert consultation (Shipper and Langston 2015). Objective characterisations also tend to be standardised and fixed in their depiction of resilience and its properties (Jones 2018). On the other side of the continuum, subjective measurement tools draw primarily on the judgement of those being evaluated themselves. This means that individuals (or a collective of individuals) are responsible for defining what resilience means to them and properties that make up a resilience person or system. These inputs are then used to guide the measurement approach that follows.

The second tenant of the objectivity-subjectivity continuum relates to evaluation. Objective approaches to resilience rely on external observation and verification – i.e. there is very little room for judgement and perspectives on the part of those being evaluated. For example, use of satellite imagery to evaluate the extent of damage to a property or assessment of household assets through a household survey can both be seen as objectively-evaluated: they involve little, if any, subjective judgement on the part the respondent. Subjective assessments make use of people's perceptions in the evaluation process. They typically involve asking respondents to self-evaluate themselves, drawing on their own internal judgement and perceived ability to deal with risk. The same approach is often used in evaluation of subjective wellbeing, where people are asked to rate their own levels of life satisfaction or happiness (OECD 2013; Dolan and Metcalfe 2012).

While these two principles act as a useful conceptual tool, in practice no one measurement tool can be considered entirely subjective or objective in nature. Indeed, most toolkits will have elements of both, with given aspects related to data collection, analysis and interpretation placed along the spectrum.

3. Methods

This paper seeks to explore relationships between objective and subjective methods of evaluating resilience by drawing on like-for-like comparisons of a number of survey modules. More specifically, we are interested in exploring three main areas of enquiry:

i. Are objective-evaluations of household resilience correlate with people's own subjective judgements, and what are the drivers associated with higher and lower resilience-capacities?

ii. Are the characteristics of objectively-evaluated resilience reflected in subjectively-evaluated scores?

iii. How do different characterisations of subjective-evaluated resilience differ. Specifically, do alternative combinations or resilience-capacities and reference to hazard-specific resilience yield different overall scores?

In order to shed light on these questions we draw on a household survey administered to 2,380 households in the Karamoja region of Northern Uganda. So as to make like-for-like comparisons between different methods of resilience measurement we employ separate objective and subjective modules administered to all households. Below we describe the modules and the methods used in constructing the respective resilience indexes.

a. Objectively-evaluated resilience module

The body of available objective toolkits for resilience measurement is large and ever-growing (Shipper and Langston 2015; Bahadur and Pichon 2016). Amongst them, one of the most commonly applied quantitative measures is the Resilience Index Measurement Analysis (RIMA), which forms the basis of the objective module for this survey. RIMA is developed by the United

Nations Food and Agriculture Organisation (FAO) and has undergone a number of iterations since its original development by Alinovi, Mane, and Romano (2008) as an econometric model for estimating household-level resilience to food security. Its latest iteration, RIMA-II, comprises a multi-dimensional objective index devised through Structure Equation Modelling (SEM), and is designed to be tailored to relate to a range of different resilience-related outcomes aside from food security (FAO 2016).

In terms of its conceptualisation of resilience, while RIMA-II acknowledges the theoretical validity of the framework supported by the Technical Working Group on Resilience Measurement (FSIN 2014), in practice it unpacks resilience capacity into four "resilience pillars":

(1) **Access to basic services**: this looks at the household's access to enabling institutional and public services environments. It includes indicators like health facilities; education; credits; water; toilet;
(2) **Assets**: this pillar includes income and non-income related assets that enable a household to make a living; it includes both productive (land; livestock; and other income generating activities); and non-productive (like house; durable assets) assets.
(3) **Social safety nets**: this refers to the network upon which a household can rely when and if faced with a shock. It includes both formal and informal transfers; the social network of solidarity and reliance.
(4) **Adaptive capacity**: this refers to "Household ability to adapt to the changing environment in which it operates" (FAO 2016, p. 14). It includes education; number of income sources; reliability of income.

Each pillar is considered a latent variable and is in turn made up of range of proxy socio-economic indicators gathered using household survey data (see Table X).

Table X: Pillars of RIMA's resilience capacities and the proxy variables used to represent them

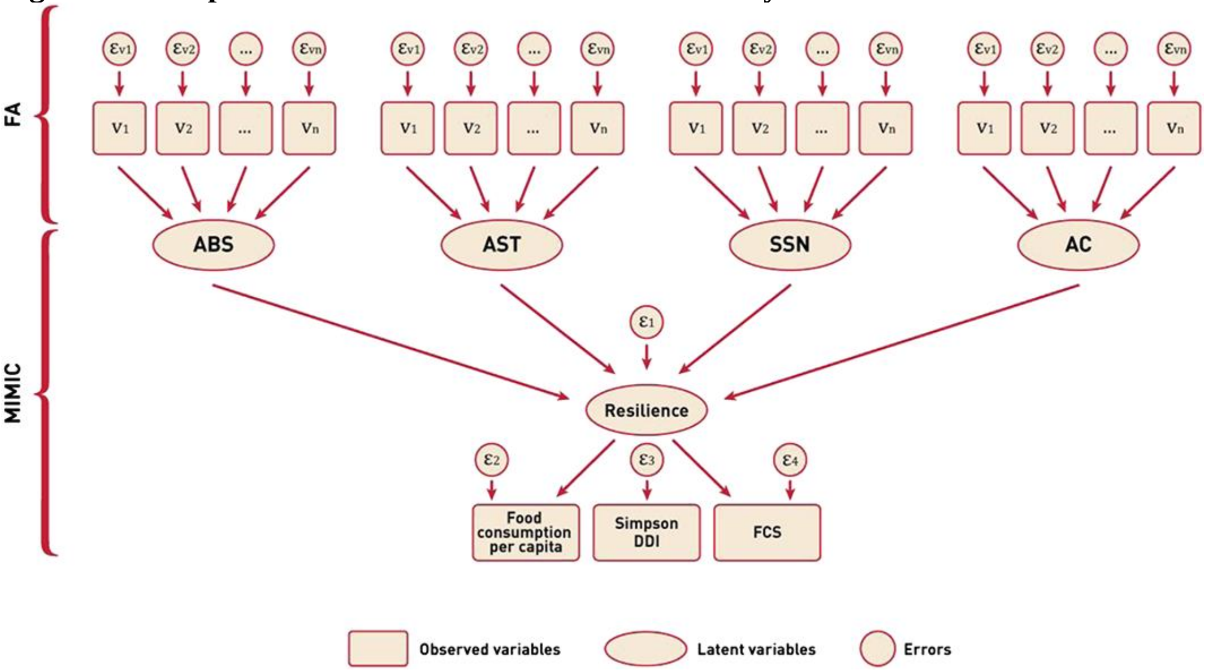
RIMA pillar	Indicators
Access to Basic Services	Household characteristics; Distance to health clinic; Distance to public transportation; Distance to markets; Access to potable water.
Assets	Wealth index; Cultivated land value per capita; Tropical Livestock Units; (TLU) per capita; Agricultural inputs.
Social Safety Nets	Cash transfers per capita; In-kind transfers per capita.
Adaptive Capacity	Levels of education; Number of income-generating activities in the household; Dependency ratio (active/non-active members);

Source: FAO 2016; D'Errico et al. 2017

In its most commonly applied format, RIMA-II is estimated through means of a two-step procedure. Firstly, a factor analysis is performed with the observed indicators assigned to each of the four RIMA pillars. Second, a Resilience Capacity Index is devised using the output of the factor analysis by means of a Multiple Indicators Multiple Causes (MIMIC) model - a type of structural equation model (SEM). The MIMIC model is comprised of both the SEM (where observed variables are considered causes of resilience as latent variable) and the measurement model (where the observed variables are considered indicators of resilience). The latter requires a reference unit: a variable assumed to be affected by a household's resilience, commonly associated with wellbeing-related metrics. Given the mandate of FAO, the chosen outcome is typically food security – often equated as combination of monthly per capita food expenditure and dietary diversity. The process allows for a single unit of resilience to be created for a household along a scale of 0 (lowest resilience) to 1 (highest resilience) using a min-max normalisation procedure.

An annotated diagram of processes employed in devising the RIMA-II score is represented in Figure X. For full details of the procedure see FAO (2016) and D'Errico et al. (2017).

Figure X: Composition and structure of the food security format of RIMA-II



Source: D'Errico et al. 2017

For the purposes of this paper, we also introduce an alternative specification of the RIMA model. This hybrid model – which we refer to henceforth as 'Hybrid-RIMA' - removes the score's tie to a food security outcome[1]. Hybrid-RIMA follows the same approach as the original RIMA-II approach but does not include the measurement part of the structural equation model. Instead it adopts a basic structural equation model to estimate the latent variable that is defined as the co-ordinated result of the four key pillars of resilience. As per the original RIMA-II approach, Hybrid-RIMA scores are normalised on a scale of 0-1.

The main advantage of this new model is that is better reflects a household's ability to sustain a range of livelihood and wellbeing outcomes in the face of external threats (i.e. their overall resilience), rather than their ability to solely maintain food security outcomes (the focus of the original RIMA model). As such, the Hybrid-RIMA model is better suited for comparison with the subjective-evaluated model which similarly focuses on overall resilience.

b. Subjectively-evaluated resilience module

For the subjectively-evaluated module of the survey we use the Subjectively self-Evaluated Resilience Score (SERS). SERS uses nine resilience-related characteristics (see Table 1). Respondents are asked to rate their levels of agreement with a series of statements provided, ranging from strongly agree to strongly disagree. Question included in the module are taken from Jones (2017) and guided by a review of resilience literature as well as a pilot exercise in Kenya in early 2017. Inherently the questions cannot cover all aspects of resilience, nor do they seek to.

[1] Note that by a theoretical point of view, a resilience indicator must be benchmarked to an outcome; otherwise we are measuring something that (we assume) could be called resilience but without being specified against a precise outcome (e.g. food security). In other words: the risk is to measure resilience to an unspecified outcome. This has been specified also in the FSIN (2014). As a consequence of this sentence and principle, SEM models have been adopted in order to specify RIMA against one outcome (food security) meaning that resilience is measured against a food security outcome, therefore defining as resilient a HH that meets its FS requirements or manage to recover over time from a shock.

Rather, they give a useful indication of subjective evaluations of a subset of resilience capacities that are known to strongly influence a household's resilience.

Table 1: List of nine resilience-related capacity questions used in the SERS model of overall resilience

Resilience-related capacity	Question	References
Absorptive capacity[2]	Your household can bounce back from any challenge that life throws at it	Béné et al. (2012) Bahadur et al. (2015)
Transformative capacity	During times of hardship, your household can change its primary income or source of livelihood if needed	Béné et al. (2012) Kates and Travis (2012)
Adaptive capacity	If threats to your household became more frequent and intense, you would still find a way to get by	Jones et al. (2010) Béné et al. (2012) Bahadur et al. (2015)
Financial capital	During times of hardship, your household can access the financial support you need	Mayunga (2007) Birkmann (2006)
Social capital	Your household can rely on the support of family and friends when you need help	Cox and Perry (2011) Aldridge (2012) Sherrieb et al. (2010)
Political capital	Your household can rely on the support politicians and government when you need help	Birckmann (2006) Magis (2010) Renschler et al. (2010)
Learning	Your household has learned important lessons from past hardships that will help you better prepare for future threats	Folke et al. (2002) Cutter et al. (2008) O'Brien et al. (2010)
Anticipatory capacity	Your household is fully prepared for any future natural disasters that may occur in your area	Paton (2003) Foster (2007) Bahadur et al. (2015
Early warning	Your household receives useful information warning you about future risks in advance	Thywissen (2006) Twigg (2009) Kafle (2012)

The SERS model is clearly an example of a subjectively-evaluated approach. However, it is important to note that, in prescribing a set of resilience-related characteristics, SERS should be classified as objectively-defined (i.e. the characteristics are selected from a review of the wider resilience literature, rather than those being evaluated themselves). The distinction highlights the non-binary nature of objectivity and subjectivity, and that most approaches will have elements of both. It also draws attention to the advantage of thinking of the relationship between the two along an objectivity-subjectivity continuum as described in Jones (2018).

Respondents were asked to score their level of agreement with each capacity using a Likert scale with 5 response items (Strongly disagree = 1, Strong agree = 5).[3] Each characteristic can therefore be compared individually, as well as allowing the generation of a collective score that aggregates across multiple capacities. Together this aggregate score constitutes a new resilience measurement tool which we term the Subjective self-Evaluated Resilience Score (SERS). SERS acts a rough marker of subjectively-evaluated overall resilience. Different variants of the SERS model can be computed based on how many, and what combination of, capacities are used to calculate the overall score. For example, a SERS model that includes all 9 resilience-related capacities is referred to as the 9-capacities (9Cs) model of overall resilience – henceforth, any references to SERS will relate to this SERS-9C model unless explicitly specified.[4] Importantly, the score also allows for resilience scores to be compared with other socioeconomic characteristics and across different social groups.

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[2] This definition of transformation used here is largely based around the ability of a household to modify livelihood activities when and if required – see Bene et al (2012) and Kates and Travis for more (2012).
[3] While numerical conversion of Likert scale responses of this type is typical across the social sciences, it is important to recognise assumptions of cardinal comparability are disputed (Kristofferson, 2017).
[4] As with any attempt to boil resilience down into a single number, caution should be used in any interpretation and application of a resilience metric.

A Cronbach's Alpha score of 0.79 suggests high internal consistency across the nine resilience-capacities (correlations between each can be seen in Supplementary Table 1). To ensure computational ease and transparency, we numerically convert answers for each of the resilience-related capacity questions and calculate an equally-weighted average mean score. As with the Hybrid-RIMA output, subjectively-evaluated resilience scores are normalised on a scale of 0-1 using min-max normalisation (higher scores indication higher resilience). While this score is neither exhaustive nor holistic in measuring a respondent's subjectively-evaluated resilience, it does provide a useful starting guide. As a robustness check, we also devise a score using an alternative weighting procedure derived from a Principal Component Analysis (PCA). As overall results appear to be almost identical between the simple averaging and PCA, we present results from the equal-weighted score in this paper (see Section 4c and Supplementary Tables 1 and 3 for further detail and comparisons).

To explore subjectively-evaluated resilience in further detail, we also look at different variants of the SERS model that reflect the different definitions and interpretations of resilience across the literature. First, we use a sub-set of the nine resilience-related characteristics to generate models of resilience that reflect widely used resilience frameworks. These included the SERS-3As variant based on Bahadur et al. (2015) which comprises of anticipatory, absorptive and adaptive capacities. It also includes a SERS-AAT variant based on Béné et al., 2012 and made up of absorptive, adaptive and transformative capacities.

c. Data

To test the relationship between objective and subjectively evaluated resilience we make use of a household survey conducted in Karamoja, Uganda in 2016 by FAO. The intendent purpose of the FAO survey was twofold: to understand the resilience capacities of communities in Karamoja; and to determine baseline values for an impact evaluation of ongoing interventions under the Joint Resilience Strategy (JRS)[5]. Indeed, a follow-up survey is scheduled to take place by 2020 resulting in a panel dataset.

The survey is composed of a total of 2,380 households. The sampling strategy is stratified according to the following five strata: (1) target households, which are those reached by the JRS in 12 parishes of the Moroto and Napak districts; (2) direct spillover households, which are those located in the remaining parishes of the Moroto and Napak districts and are not involved in the JRS; (3) indirect spillover households, which are those located in the two districts where the JRS is not actually operating (Kotido and Nakapiripirit) but where other UN projects are ongoing; (4) a 'different ethnicity' group, which includes households located in two districts (Abim and Amudat) populated with ethnic groups that are different from the Karamojong; (5) and the pure control group, comprised of households located in the Kaabong district, which have the same ethnic group and socioeconomic conditions, mostly pastoralism, as the target group, but which are not involved in the JRS.

The household questionnaire is comprised of a range of thematic sections and piloted in Moroto in November 2016. Specifically, it collects detailed information on household characteristics, including food and non-food consumption, shocks, coping strategies, and so on. Much of the socio-economic data was then used to compile the RIMA and Hybrid-RIMA indexes, and compared with subjective evaluations of household resilience.

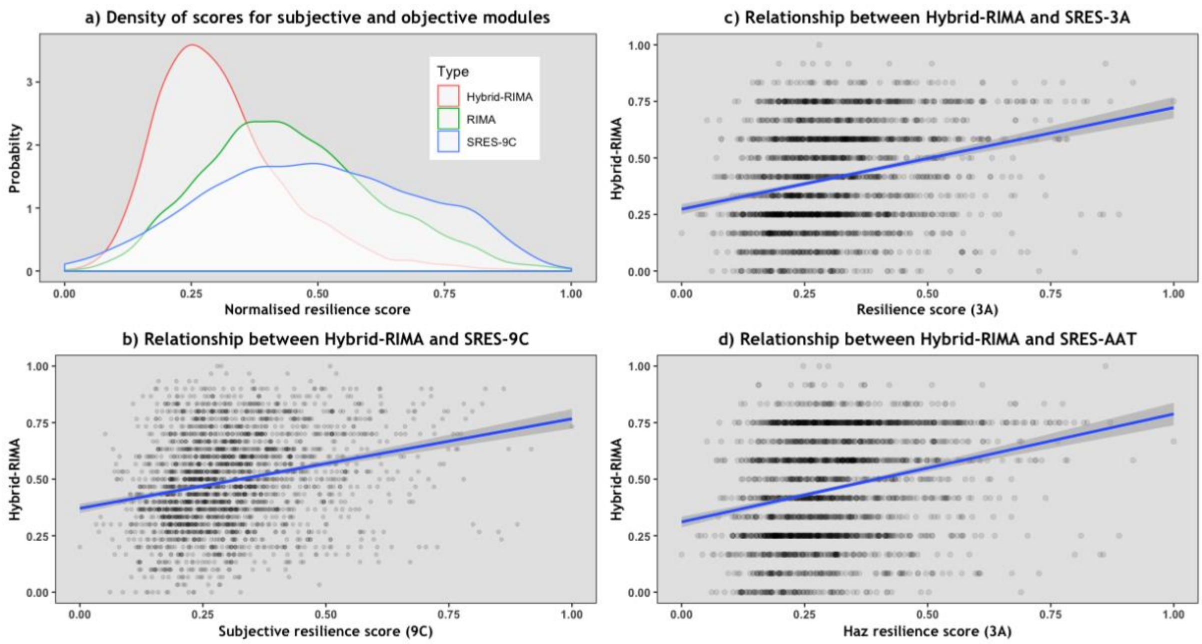
[5] For more information on the types of activities supported under the JRS and its evaluation see http://www.fao.org/3/ca0345en/CA0345EN.pdf

4. Results

a. Descriptive analysis

In observing responses to objective- and subjectively-evaluated resilience in the Karamoja survey, a number of commonalities and differences are clear. The first thing to note is that the distribution of objective scores (centered on a mean of 0.311) is far narrower than that of the subjective scores (with a mean of 0.49) (see Figure 1a). This may be due the fact that the Hybrid-RIMA approach is comprised of a narrow set of pre-defined objective parameters. Yet, the wide and normal distribution of the SERS scores is marked. Indeed, it suggests that – at least from the perspective of the individual – levels of resilience are far more varied than assumed from the RIMA model of resilience. It may also reflect a greater number of confounding factors that affect people's self-assessed scores (a factor we return to later). Intriguingly, the adjustment from the original (food-security oriented) RIMA-II to Hybrid-RIMA is responsible for much of the leftward shift in distribution, with the former aligning much more closely to the subjective module than the latter[6].

Figure 1: Densities and relationship between Hybrid-RIMA and subjective modules



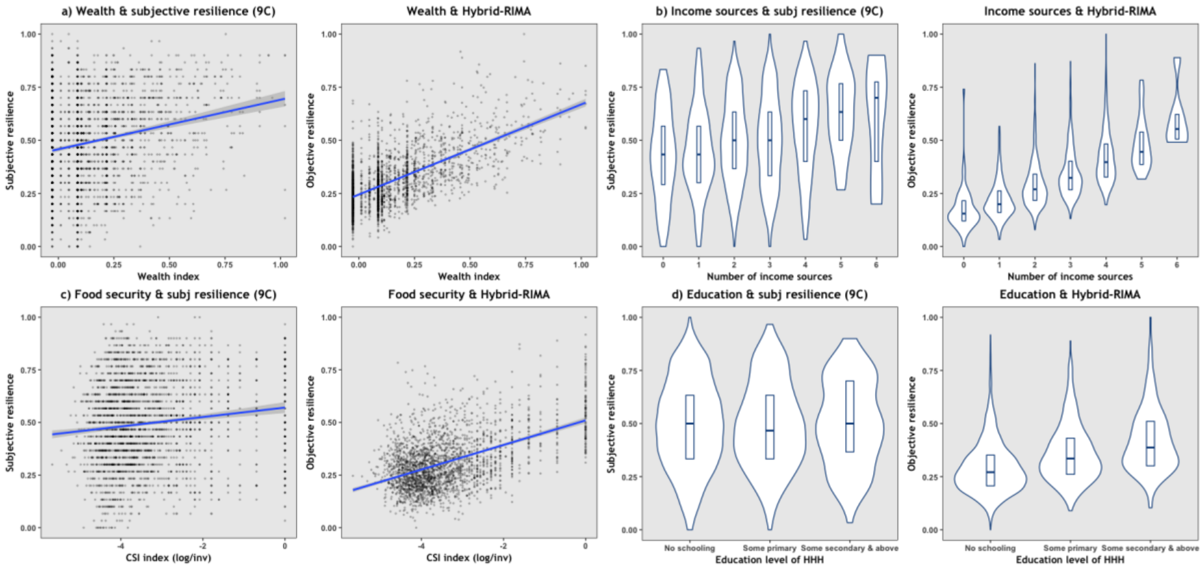
Despite this, Hybrid-RIMA and subjectively-evaluated scores demonstrate relatively strong positive relationships. This is the case not only for resilience as depicted under the SERS-9C model ($r^2=0.26$), but the SERS-3A ($r^2=0.28$) and SERS-AAT models too ($r^2=0.28$) (see Supplementary Table 2). For further comparison of various objective and subjectively-evaluated models, including RIMA and SERS-PCA variants, see Supplementary Table 2. As is clear from Figure 1, though the relationship between the two metrics is positive, a considerable degree of variation.

A key interest in comparing objective- and subjectively-evaluated approaches is associations with core drivers of household resilience. For example, much of the literature cites the accumulation of asset wealth as a strong determinant of a household's ability to deal with disturbance (Tyler & Moench 2012; Cutter et al. 2008). Interestingly, both subjective and objective modules demonstrate positive relationships (as shown in Figure 2a) with higher wealth accumulation

[6] Note that direct comparisons between the original RIMA-II model and SERS can be found in Supplementary Table 4

corresponding to higher levels of resilience. Similar positive associations are apparent for diversity of incomes sources as well as food security (represented by the CSI index[7]), both traditionally considered as core drivers of resilience at the household level (Adger 1999; Jabeen 2010). Not all assumed associations are common however. For example, while the highest level of education for household heads shows a marked positive association under the objectively-evaluated resilience module, no such association is apparent for the subjective module[8].

Figure 2: Relationships between objective and subjectively-evaluated modules and key socio-economic variables



b. Multivariate analysis

i. Do the drivers of subjectively-evaluated resilience reflect those for objectively-evaluated resilience?

While descriptive and univariate analysis is useful in uncovering broad associations, it is important to control for the effects of confounding factors before drawing firm conclusion. As such we run a series of OLS regression models with SERS and Hybrid-RIMA as the two dependent variables. A range of socio-economic variables – each considered to have a degree of association with resilience within the resilience literature – are gathered from the remainder of the survey modules and serve as independent variables within the models. Both models include area fixed effects with standard errors clustered at the sub-county level. In comparing a range of different setups, we also look at outcomes from regressions models using simple Ordinary Least Squares (OLS) with area fixed effects removed, area-fixed effects with robust standard errors and multi-level models with households nested within sub-countries and districts – see Section X.

$$SERS\_9C_{hc} = \alpha_c + \beta_1 SHOCK_{hc} + \beta_2 DRIVER_{hc} + e_{hc} \tag{1}$$

The primary OLS area-fixed effects set up is presented in Model 1. Here the outcome $SERS\_9C_{hc}$ relates to the 9C variant of the SERS model indexing households h in sub-county c. $SHOCK_{hc}$ is a vector of dummy variables for a series of self-reported shocks at the household-level, while $DRIVER_{hc}$ is a vector of socio-economic variables commonly associated with drivers of resilience

[7] CSI is an indicator of household food security that uses a series of questions about how households manage to cope with a shortfall in food for consumption results in a simple numeric score. In its simplest form, monitoring changes in the CSI score indicates whether household food security status in declining or improving (see Maxwell et al. 2003)
[8] We return to the relationship between education and resilience in more depth in Section 5a.

at the household level. $\alpha_c$is shown as sub-county fixed effects (expressed as dummies) with the error term represented by e.

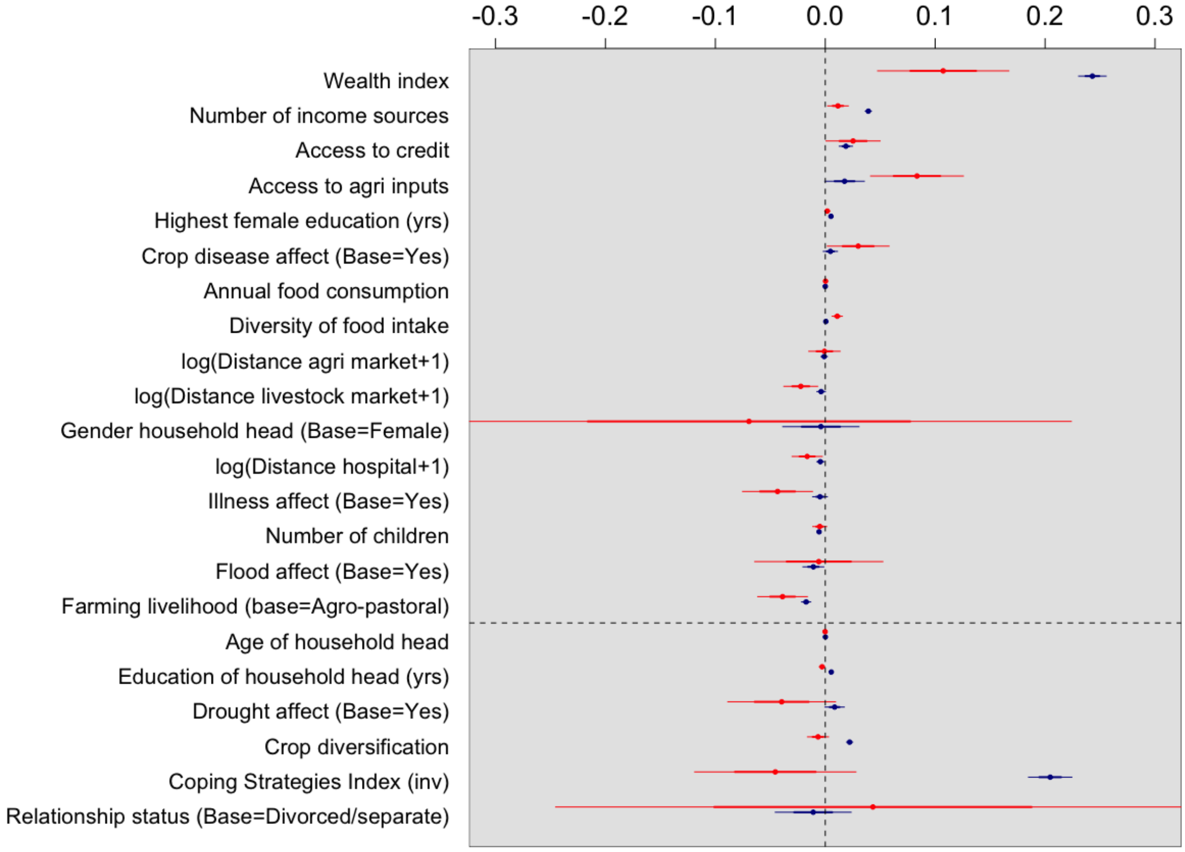
Outputs from the above are compared directly with Model 2. This model shares an identical structure to that of Model 1, simply replacing Hybrid-RIMA as the outcome variable of interest.

$$RIMA_{hc} = \alpha_c + \beta_1 SHOCK_{hc} + \beta_2 DRIVER_{hc} + e_{hc} \tag{2}$$

In effect, outputs from Model 2 are somewhat uninteresting in isolation; results simply inform us of the assumptions and weights assigned to various indicators that feed into the RIMA approach. Instead, the real utility comes from side-by-side comparisons of Models 1 and 2. Given that the SERS approach does not factor any of the shock or driver variables into the formulation of the overall score, comparative outcomes of the two models serve as a quasi-independent check of the RIMA set-up. In theory, if both scores are wholly reflective of the same underlying property (and are void of bias) then we would expect similar trends and effects from the variables of interest. Though in practice it may be difficult to argue that RIMA and SERS are capturing an identical latent construct (i.e. overall household resilience), they undeniably overlap and should be expected to broadly reflect the same associations with relevant drivers of resilience.

Indeed, the first thing that is clear in comparing marginal effects between the two models (Figure 3) is that many of the assumed drivers of resilience show similar associations – both in terms of sign and significance. For example, wealth appears to have the strongest positive influence on both RIMA and SERS – though it should be noted that the effect is somewhat lower for the latter (roughly half). Some reassurance can be taken from this result as asset wealth is one of the most commonly referred to drivers of household-level resilience across a range of resilience literatures – both qualitative and quantitative (Adger 1999; Carter et al. 2004; Bene et al. 2012). Other commonly associated drivers showcase significant positive influences across both models, including: number of income sources (often used as proxy for livelihood diversity); access to agricultural inputs; and access to credit. For more detailed breakdown and comparison of model outputs see Supplementary Table 3.

Figure 3: Coefficient plot comparing the influence of common drivers of resilience on RIMA (blue) and SERS (red) outcomes



Notes: Dots represent beta coefficients, standard errors are repressed are thick whiskers with 95% confidence intervals expressed as thin whiskers (variables with CIs that do not include 0 are considered significant at the p<0.05 level). Standard errors are clustered at sub-county level. Variables below the horizontal dotted line correspond to those that disagree in sign for either of the two models.

A number of common significant negative associations are also apparent. For example, households that reside further away from a hospital are linked with lower RIMA and SERS scores. While this potentially showcases the importance of access to medical services, it is also important to note that hospitals in the area are largely found in urban areas and may be confounded by other unobserved variables. Higher numbers of children are also seen to negatively affect objective and subjectively-evaluated resilience scores (though the latter is not statistically significant at the 0.05 level). This is potentially linked with higher dependency on household bread-winners during times of need (Vaitla et al. 2012; Malone 2009). Interestingly households reliant on farming as their primary source of livelihood appear to have lower scores than agro-pastoralists. The negative relationship may point to the benefits accrued by agro-pastoralists in being able to more easily reallocate assets and livestock in search of more favorable climes during times of drought (and other hardships) (Opiyo et al. 2015). Indeed, the finding is particularly relevant in light of ongoing political and academic debates over tradeoffs between pastoral and settled livelihoods in Karamoja, with many development actors having historically portrayed nomadic pastoralism as a particularly vulnerable and unviable source of livelihood in the region (Levine 2010).

While it is clear that many of the core drivers associated with RIMA and SERS overlap, there are a few areas that showcase interesting differences. Perhaps the largest of these is in relation to food security. Measured using the Coping Strategies Index (CSI) – a measure of the number of coping strategies used by a household within the last month to address short shortage or malnutrition – model outputs show that the adoption of more coping strategies is associated with higher RIMA scores (i.e. the less food insecure a household is the more likely the household is to be resilient). This association is strongly significant and has a large positive effect on RIMA outcomes. Correspondingly, the inverted CSI has no significant association with SERS scores. If anything, the relationship appears to be negative (though with wide confidence intervals). We return to discuss this apparent contradiction in Section 5.

Another example of dissimilar associations relates to the highest level of education within the household. This has a positive and highly significant association with RIMA (remember that in large part this reflects the set-up and weightings given to the RIMA model). In contrast, education has a significant negative relationship with SERS scores – though it is worth noting that the size of effect is marginal. Likewise, crop diversification has a significant positive association with RIMA but no such relationship with regards to SERS scores.

ii. Are the characteristics of objectively-evaluated resilience reflected in subjectively-evaluated scores?

In order to examine whether the characteristic of objectively-evaluated resilience (i.e. the broad components of resilience) are reflected in subjectively-evaluated scores we run an OLS model (Model 3) with SERS as the outcome variable, $SERS\_9C_{hc}$. As with prior models, we include area-fixed effects and cluster standard errors at the sub-county level. Under the Model 3 specification the four characteristics of resilience RIMA[9] are used as independent variables, consisting of: assets, AST_{hc}; access to basic services, ABS_{hc}; social safety nets, SSN_{hc}; and adaptive capacity, AC_{hc} (see FAO 2016 and D'Errico et al. 2017 for a full list of indicators with each pillar).

$$SERS\_9C_{hc} = \alpha_c + \beta_1 AST_{hc} + \beta_2 ABS_{hc} + \beta_3 SSN_{hc} + \beta_4 AC_{hc} + e_{hc} \tag{3}$$

Outputs from Model 3 are compared directly with a parallel model that replaces scores from the SERS subjective model with that of RIMA, $RIMA_{hc}$.

$$RIMA_{hc} = \alpha_c + \beta_1 AST_{hc} + \beta_2 ABS_{hc} + \beta_3 SSN_{hc} + \beta_4 AC_{hc} + e_{hc} \tag{4}$$

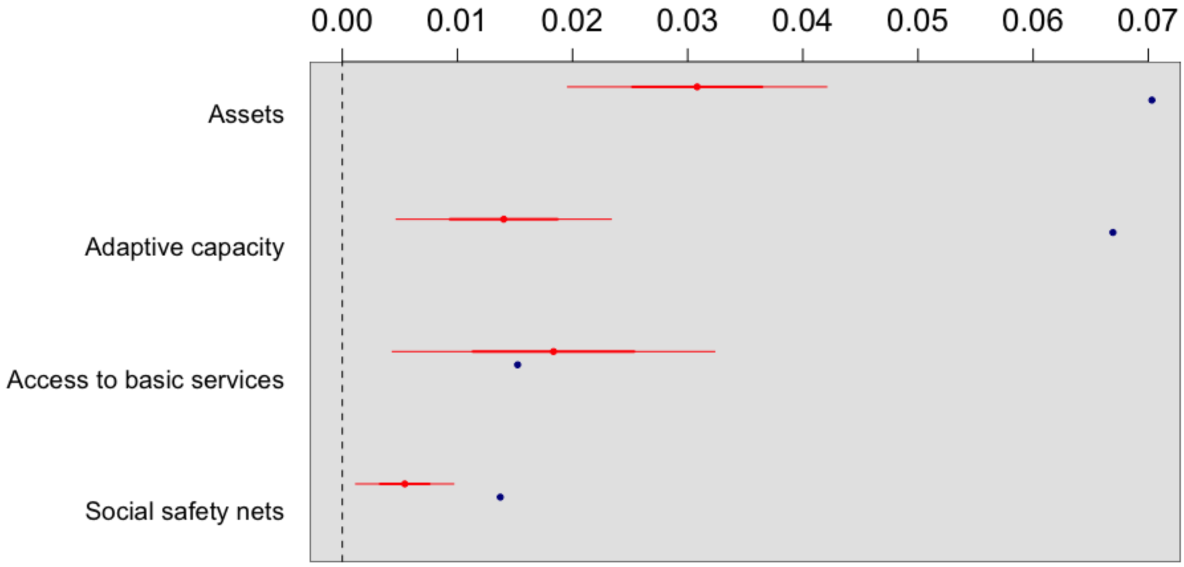
Outputs from the two models are shown in Figure 4. Again, simply observing Model 4 is not particularly informative. It mainly demonstrates the weightings assigned to each of four characteristics of resilience as specified within the RIMA approach. It is also unsurprising that the confidence intervals are very narrow and statistically significance given that the four characteristics are fully predictive of the RIMA score. However, when comparing the Models 4 and 5 together it is apparent that all four components share similarities between objective- and subjective-evaluated outcomes. For a start, all four pillars positive, with assets having the largest marginal effect and social safety nets the lowest. One notable qualitative difference is the magnitude of effect for adaptive capacity which is higher for SERS than for RES – this may in part reflect the difficulty of measuring a particularly multi-faced characteristic with a handful of objective indicators.

Importantly, results from the side-by-side comparison may suggest that the four pillars chosen under the RIMA specification are somewhat consistent with regards to people's self-evaluations of their household's resilience. Indeed, the objective variables that constitute the four pillars are not factored into the SERS set-up and can therefore be loosely considered as a loosely independent check. It is also worth noting the that the effect sizes for RIMA are far higher than SERS, with the exception of access to basic services. While this may imply that objective approaches are overweighting the respective characteristics, we note that unlike RIMA (which is composed solely of the four characteristics), SERS is as self-assessments and unlimited in the

[9] Note that FAO use the term 'pillars' rather than characteristics

range of characteristics that the individual may choose in their evaluation. It is therefore not surprising that RIMA's characteristics are somewhat less predictive of SERS scores.

Figure 4: Coefficient plots showing associations between RIMA (blue) and SERS (red) relative to RIMA's four characteristics of resilience

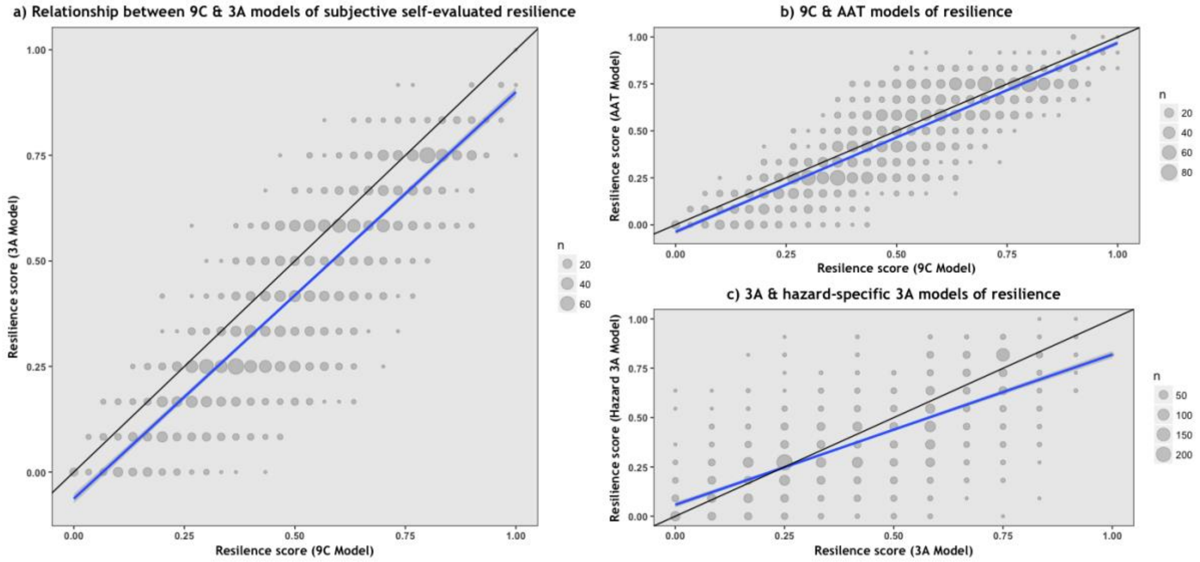


Notes: Dots represent beta coefficients, standard errors are repressed are thick whiskers with 95% confidence intervals expressed as thin whiskers (variables with CIs that do not include 0 are considered significant at the p<0.05 level). Standard errors are clustered at sub-county level.

iii. Do different types of subjectively-evaluated resilience produce similar outcomes?

The paper's final research query seeks to compare the outcomes of different formats of subjective scores. More specifically, comparisons between variants of subjectively-evaluated scores of resilience. As is clear from Figure Xa, a strong correlation exists between the 9C and 3A variants of the SERS model for overall household resilience (R^2=0.88). A similar association is also apparent when comparing 9C and AAT variants in Figure 5b (R^2=0.87). While there is greater spread, comparison of the 3A model of overall resilience and the 3A hazard-specific variants also demonstrate high correlation (R^2=0.72). Indeed, the lower relative correlation in Figure 5c is not altogether surprising given that they are not necessarily targeting the same latent property (a household's resilience to a drought may be somewhat different to their ability to deal with a collection of overall risks). By way of an interesting point of comparison, the relationship between the original RIMA specification (the variant of RIMA that is tagged specifically to a food security outcome) and Hybrid-RIMA (which has no outcome variable and is therefore a better reflection of overall resilience) is notably weaker with an R^2 of 0.46.

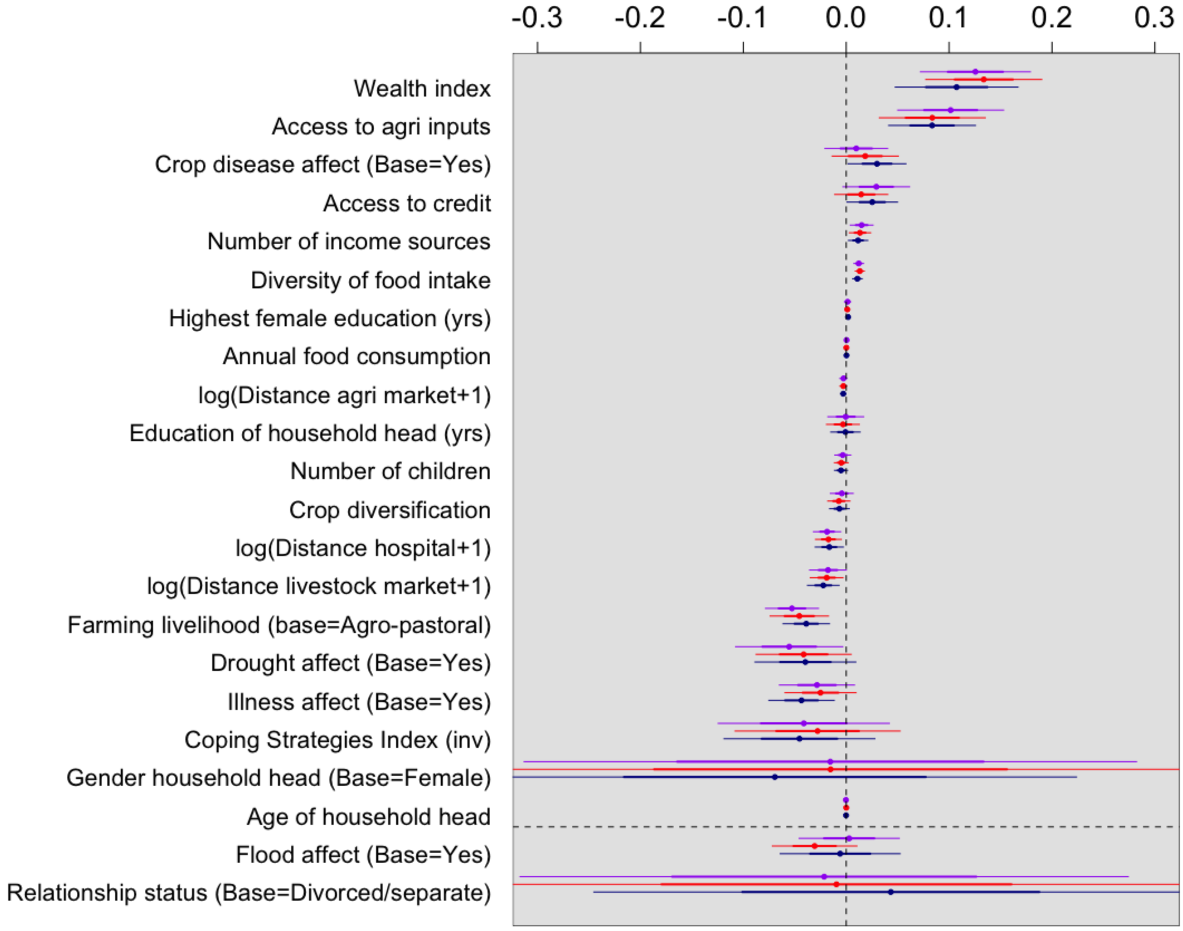
Figure 5: Count plots of relationship between different variants of subjectively self-evaluated resilience



The size of dots represents the frequency of responses with the same score. Note that all models in figures a) and b) are in relation to overall resilience, figure c) compares and a model of overall resilience with a hazard-specific model.

While subjective variants appear to be highly correlated, what about the similarities between underlying drivers? As with the analysis above we perform a series of OLS regressions that allow for side by side comparisons between the three main variants of SERS subjectively-evaluated resilience approach. Specifications for these models are identical to Model 1 except that the outcome variable is replaced by the 3A and AAT variants of overall resilience respectively. As apparent from the coefficient effects plots in SM Figure 2, associations between subjective self-evaluations of resilience and various drivers and shocks remain notably similar across the three variants. Indeed, there are only a small number of variables that do not exhibit the same sign and level of statistical significance. Moreover, the two with opposing signs – whether the household has experience a flood in the past 12 months and relationship status of the bread-winning couple – have such wide confidence intervals that little can be inferred about the differences.

Figure 6: Coefficient plot comparing different variants of the SERS subjectively-evaluated resilience model



Notes: Dots represent beta coefficients, standard errors are represented as thick whiskers with 95% confidence intervals expressed as thin whiskers (variables with CIs that do not include 0 are considered significant at the p<0.05 level). Standard errors are clustered at sub-county level. Variables below the horizontal dotted line correspond to those that disagree in sign for either of the two models. Blue line = SERS-9A; Red line = SERS-3A; Purple line = SERS-AAT.

c. Robustness checks

In order to test the validity of the paper's assertions we perform a number of robustness checks. As mentioned earlier, alongside the OLS model with area-fixed effects we also run various other regression set-ups to examine the consistently of our results. Accordingly, Supplementary Table 3 shows comparisons of Hybrid-RIMA and SERS when run using OLS with no area-fixed effects (1 and 5), OLS with area fixed effects (2 and 6), OLS with area fixed effects and clustered standard errors (3 and 7, and the main models used in the manuscript) and a multi-level model that nests households within sub-counties and district (4 and 8). All OLS models feature robust standard errors unless otherwise stated. Though there are some apparent differences in the size of standard errors (notably in relation to the effect of crop diseases), all four models appear to be relatively consistent, lending weight to the outputs present.

Another important step taken in our analysis is the use of a modified version of the RIMA approach. Hybrid-RIMA is deemed a more suitable comparison with SERS as it better reflects overall resilience and is no longer tied to a food-security outcome. Yet, we recognise that the original RIMA tool is well established within the literature and often used as a proxy for wider resilience outcomes (not just food security). Therefore, we run the same model set-ups as before, using the original RIMA-II instead of Hybrid-RIMA as the outcome variable. Results are presented in Supplementary Table 4 with a similar range of regression runs as specified SMT3. Some differences are noted between the two set-ups, though most are unsurprisingly in relation to food-related variables such diversity of food intake, annual food consumption and crop diversification.

An important factor in determining multi-question scales is the weightings assigned. While we use an equally weighted average for most of the results presented in the paper, we devise a variant (labelled SERS-PCA) that weights resilience-capacities according to the first principal component (with 8 questions retained). Accordingly, Supplementary Table 5 re-runs comparisons between RIMA and SERS-PCA instead of SRES-PCA. Again, we find few differences. Lastly, we note that a weakness of many subjective evaluations is a tendency for respondents to agree with all questions or provide similar answers throughout a survey – known as acquiescence bias (OECD 2013). To account for this, we remove any household from the sample that provides the same answer across each of the resilience-related capacity questions. When Model 2 is rerun under this set-up we see no qualitative differences (see Supplementary Figure 2).

5. Discussions and conclusion

Results from our Karamoja survey point to a number of interesting findings and discussion points. Below we highlight four main areas that have significant implications for efforts to conceptualise, observe and measure resilience.

a. Subjective and objectively-evaluated resilience share many similarities as well as notable differences

Like-for-like comparisons of SERS and RIMA models reveal that many drivers commonly associated with household-level resilience have similar influences on subjective and objective forms of evaluation (Figures 2 and 3). This applies to both to the sign and magnitude of associated effects. Drivers include factors like: asset-wealth; diversification of income sources; livelihood type; household size and composition; and access to basic services and safety nets. Each have a rich history of association amongst the wider resilience literature (Tyler & Moench 2012; Cutter et al. 2008; Adger 1999; Jabeen 2010). In many ways this is reassuring, as it suggests that both approaches to measurement may be picking up on similar trends affecting the same underlying properties of household resilience[10]. It also provides some reassurance in the selection of a large number of indicators used in objective measures of resilience. This notion is further supported by the fact that all four pillars of the RIMA model are not only positively associated with SERS scores, but follow somewhat similar rank orders (Figure 4).

These findings are all the more significant as the two modules are in many ways independent of each other. None of the indicators that make up the RIMA model are used to compute the SERS scores, and aside from potential priming effects, there is nothing to systematically encourage respondents to respond similarly across the two modules - indeed, given the size and complexity of the RIMA module this would be a considerable undertaking.

Having pointed to the similarities, there remain a number of notable differences between drivers of both approaches. One of the most surprising is the lack of positive association between SERS and the highest level of education for head-of-household (which is insignificant and has a negative coefficient). By contrast, education levels have a strong positive association with RIMA scores. This reflects of much of the wider resilience literature which assumes that higher levels of

[10] Again, it is worth noting that despite efforts to ensure that the design and conceptualisation of the SERS and RIMA models are identical in outlook, without a common outcome variable to compare against it is not possible to verify whether either is tapping into the same properties of resilience (we hope to answer this question in a forthcoming survey).

education are not only reflective of a household's capacity to adapt to changing risks, but greater levels of resilient behavioural attitudes and heightened awareness of current and future risk faced by the household (Pissello et al. 2017).

The lack of association between education and subjectively-evaluated resilience may be partly explained by the environmental and socio-economic conditions of the area. Karamoja is an arid landscape frequently affected by drought. Nomadic livelihoods therefore have some advantages as they are able to relocate during times of hardship (Opiyo et al. 2015; Levine 2010) – this is underscored by the fact that pastoralists have higher SERS scores than farmers. While formal levels of education may benefit households in the area, it is unlikely to provide little added benefit when compared with local informal and indigenous knowledge gained in coping with persistent drought (particularly once controlling for income or asset wealth). Interestingly, a similar lack of association between subjectively-evaluated resilience and formal education is observed across a number of other subjective assessments by Jones and Samman (2016); Bene et al. 2016; and Claire et al. (2018). More can therefore be done to examine the relationships between formal and informal education and their inclusion in resilience metrics. Together this suggest that a greater understanding of the links between education and household resilience is needed before strong conclusions can be drawn, particularly in justifying its inclusion in resilience metrics.

One interesting finding relates to prior experience of shock events. From a conceptual point of view, households that are able to buffer and prevent shocks from affecting them are often assumed to have higher levels of overall resilience. In theory, such households demonstrate greater capacity to mobilise the resources and capabilities needed to fend off a shock, particularly associated with the concepts of exposure and sensitivity (Kahn 2005; Ibarraran et al. 2009). Moreover, it is commonly assumed that households that are repeatedly prone to shock events have lower relative levels of resilience compared to those that are not as susceptible as, over time, repeated shocks wear away at the household's ability to deal with future risk (Silbert & Useche 2012). However, findings from the Karamoja survey suggest that self-reported experience of prior shock events is negatively associated with subjective assessments of resilience: those that have recently experienced a shock have higher levels of subjectively-evaluated resilience. This trend runs true across a number of shock types.

In the context of the Karamoja survey, drought is perhaps the most relevant stressor to consider. As is clear from Figure 3, households that report experiencing a drought in the 12 months prior have subjectively-evaluated resilience scores that are higher than those that have no such experience, when controlling for a range of other relevant factors (effects are significant at $p<0.05$ for 2 of the 4 models used). Similar negative associations are associated with household members having experienced illness as well as flooding (while the latter is insignificant it should be noted that flooding Karamoja is a rare occurrence). On the other hand, prior experience of crop disease is negatively associated with subjectively-evaluated resilience (significant at $p<0.05$ for 3 of 4 models).

While these relationships may seem somewhat counterintuitive at first, there are conceptual and practical grounds to defend such an association. Households that have experienced a recent shock may be in a better position not only to gain valuable insights into the relevance and suitability of the coping mechanisms adopted, but may be better able to anticipate and adapt to future risks using knowledge gained in recovery (Berkes and Turner 2006). Contrastingly, households that have no prior experience of a shock may be comparably ill-prepared given the unfamiliarity of anticipatory and coping strategies needed to respond. Existing literature on risk perception on the issue is mixed. Wachinger et al. (2013) highlight examples (such as Ruin et al. 2007; Ming-Chou 2008; and Mirceli et al. 2008) of how direct experience of a natural hazards lead to an overestimation of future risk and a greater sense of dread. Contrastingly, other examples (such as Hall et al. 2009 and Scolobig et al. 2012) point to prior experience as leading to belief that future events are unlikely to affect them and thus lower risk perception.

The points above point to the likelihood of such effects being highly context specific. We therefore suggest that our finding should be interpreted with caution – particularly in extrapolating conclusions to other geographic areas. We also note that differences in levels of significance vary across the four model set-ups (see Supplementary Table 1). However, while a significant proportion of resilience financing amongst the international development community is (rightly) focused on reducing exposure to shocks, results from the survey tentatively suggest that exposure is positively associated with a household's perceived resilience capacities. While it may not be advisable to suggest that development agencies actively encourage greater exposure to shock events, it may signal interventions aimed at supporting resilience-building are best focused on enhancing resilience capacities and sensitivity to shocks (alongside action to limit exposure).

b. Different characterisations of subjectively-evaluated resilience yield similar results

Another interesting result is the commonality across different variants of subjectively-evaluated resilience modules. As evidenced in Figures 5 and 6, the three variants of the SERS model (3A, AAT and 9C) each appear to be very highly correlated. Moreover, the associations between different SERS variants and potential drivers of resilience overlap considerably, particularly with regards to the sign and magnitude of influence (Supplementary Table 6). This is important given the considerable amount of attention that contested definitions and characterisations of resilience occupies within the wider academic literature.

As alluded to in Section 2, resilience can (and has) been chopped up in myriad ways. The implication being that the choice of which resilience-related capacities to include will have considerable implications for how resilient a person or household is deemed. Yet, using two popular resilience frameworks that feature heavily (3A and AAT), as well as a much larger set of 9 capacities drawn across the wider literature (9C), we find very similar results and associations amongst the three. This may present a challenge to evaluators, and lessen the burden placed on choosing the mix of resilience-related capacities used in measurement approaches. It may also suggest that shorter subjective modules may be able to accurately reflect larger more comprehensive ones. This is of critical importance in trying to save survey space and reduce the time needed in interviewing households.

c. Recognising biases and limitations

Importantly, these results must be interpreted with a degree of caution. With any type of perception-based survey such as this, there may be a number of cognitive biases that may be affecting results. For one, placement of the overall and hazard-specific modules was close in the order and respondents may well have been primed to respond in similar manners. This is especially relevant given the similarity of wording and response-items. Questions within the same module also followed the same sequence and may have resulted in further priming and cognitive fatigue. More needs to be done to test associations and account for cognitive effects before firm confidence in the conclusions can be drawn. Practices such as the reverse coding of response-items, randomisation of question and module order as well as use of anchoring vignettes may be an important next step and are planned in future iterations of this research.

d. Combining strengths of different approaches

While we demonstrate clear links between objective and subjectively-evaluated resilience modules, a number of notable differences are apparent. In part, this is likely to be reflected by different strengths and weaknesses inherent in each respective approach. For one, objectively evaluated approaches struggle to account for many of the 'softer' elements that support household resilience (Levine 2014). Though subjective tools are by no means a silver bullet, they may prove of considerable use in combination with traditional objective approaches, given that aspects such as social capital, entitlement and power can be more readily incorporated (Jones and Tanner 2017).

Conversely, the addition of objectively-evaluated modes of assessment may add considerable weight in instances where strong cognitive biases, such as social desirability or priming, may be affecting subjectively-oriented evaluations. It is therefore important to build on findings such as these, and establish whether respective approaches may offer the most value, either in combination or used alongside each other.

Supplementary Material: Whose resilience matters? Like-for-like comparison of objective and subjective evaluations of resilience

In accompanying the main manuscript, we present various additional tests and plots that support the report's findings. Details of each are presented below.

SM Table 1: Here we show a matrix of Spearman's rank correlation coefficients between the 9 subjectively-evaluated resilience capacities presented in Table 1 (see main manuscript).

SM Table 2: This table features Spearman's rank correlations between a range of objectively- and subjectively-evaluated resilience. More specifically, the various models include: Hybrid-RIMA, a stripped-back version of RIMA that is decoupled from a food security outcome (and hence a better comparison with overall resilience); RIMA, the principal FAO model outlined in FAO (2016) tied to a food security outcome; SRES-9C, which uses an equally weighted average of all 9 resilience related capacities; SRES-PCA, which weights subjectively-evaluated scores using a principal components analysis; SRES-3A, which uses a subset of 3 subjectively-evaluated questions related to Absorptive, Adaptive and Anticipatory capacities (see Table 1 in main manuscript); and SRES Hazard-specific model , which features questions tied to a specific hazard – in this case drought (as opposed to overall resilience). The latter features the same resilience-capacities as SRES-3A and is based on methods used by Jones et al. 2017.

List of three resilience-related capacity questions used in the 3As hazard-specific model of resilience

Resilience-related capacity	Question
Anticipatory capacity	If a [flood/drought/cyclone] occurred in the near future, how likely is it that your household would be fully prepared in advance?
Absorptive capacity	If a [flood/drought/cyclone] had recently ended, how likely is it that your household could fully recover within six months?
Adaptive capacity	If [floods/droughts/cyclones] were to become more frequent and severe in the future, how likely is it that your household could deal with the new threats presented?

Adapted from Jones et al. 2017

SM Table 3: Here we present a range of model outputs each with similar setup featuring either Hybrid-RIMA (Models 1-4) or SRES-9C (Models 5-8) as the dependent variable as well as a series of socio-economic variables as independent variables. Regression coefficients are presented in each cell with standard errors in parentheses. Models 1 and 5 (labelled OLS) run an ordinary least squares regression with robust standard errors. Models 2 and 6 (labelled Fixed effects) run a linear regression model with sub-country fixed effects and robust standard errors in parentheses. Models 3 and 7 (labelled Fixed effects CRS) feature a similar set up with robust standard errors clustered at the sub-country level. Models 4 and 8 present a multi-level regression model with sub-county random effects nested within districts.

SM Figure 1: This shows a coefficient plot of the same variables and model set-up presented in Table 3

SM Table 4: This features an identical model setup to SM Table 1, comparing a range of regression models. In this case, however, the dependent variables include the original RIMA (Models 9-13), with SRES 9C (Models 14-18) featured for ease of comparison. Aside from the choice of dependent variable, model specifications of Models 9-18 are identical to those of Models 1-8 (SM Table 1).

SM Table 5: As above, this table runs model setups that mimic SM Tables 1 and 2. Here the dependent variable for the subjectively-evaluated models (Models 21-24) feature the SRES-PCA variant, with weights assigned via principal component analysis rather than equal weighting between resilience-related capacities. Aside from the choice of dependent variable, Model specifications of Models 9-24 are identical to those of Models 1-8 (SM Table 1).

SM Table 6: Here we present outputs comparing the various subjectively-evaluated models of overall resilience. These include models with the following dependent variables: SERS-9C model with equal mean weighted across all 9 resilience-related capacities; SERS 3A with equal mean weights for Anticipatory, Absorptive and Adaptive capacities (following Jones et al 2017 and Bahadur et al. 2015); SERS AAT with equal mean weights Absorptive, Adaptive and Transformatory capacities (following Bene et al. 2012); and SERS 9C with households that respond with the same answer across each resilience-related capacity removed from the sample.

SM Table 1: Correlation matrix of subjectively-evaluated resilience-related capacities used in the SRES model of overall resilience

	Absorptive capacity	Adaptive capacity	Transformative capacity	Financial Capital	Social capital	Political capital	Learning capacity	Anticipatory capacity	Early warning
Absorptive capacity	1	0.636	0.506	0.459	0.244	0.084	0.456	0.467	0.253
Adaptive capacity	0.636	1	0.499	0.409	0.283	0.077	0.445	0.422	0.325
Transformative capacity	0.506	0.499	1	0.420	0.206	0.046	0.361	0.395	0.305
Financial Capital	0.459	0.409	0.420	1	0.099	0.074	0.314	0.491	0.276
Social capital	0.244	0.283	0.206	0.099	1	0.160	0.219	0.153	0.171
Political capital	0.084	0.077	0.046	0.074	0.160	1	0.117	0.070	0.165
Learning capacity	0.456	0.445	0.361	0.314	0.219	0.117	1	0.456	0.355
Anticipatory capacity	0.467	0.422	0.395	0.491	0.153	0.070	0.456	1	0.352
Early warning	0.253	0.325	0.305	0.276	0.171	0.165	0.355	0.352	1

SM Table 2: Correlation matrix of variants of the RIMA (objectively-evaluated) and SERS (subjectively-evaluated) models

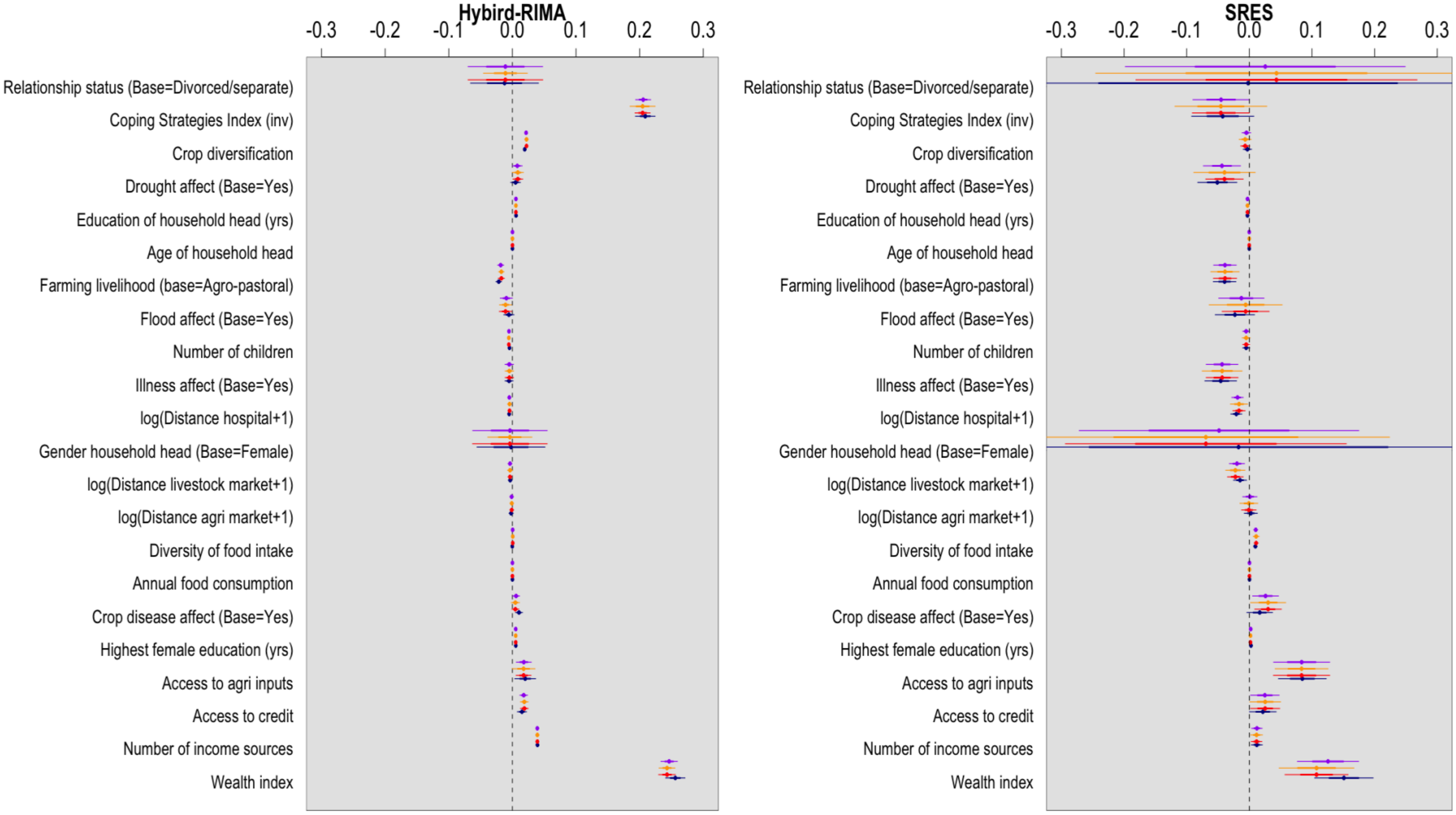
	Hybrid-RIMA	RIMA (food security)	SRES-9C	SRES-PCA	SRES-3A	SRES-AAT	SRES-Drought (hazard-specific)
Hybrid-RIMA	1	0.462	0.258	0.258	0.275	0.275	0.222
RIMA (food security)	0.462	1	0.264	0.250	0.268	0.277	0.199
SRES-9C	0.258	0.264	1	0.917	0.877	0.868	0.693
SRES-PCA	0.258	0.250	0.917	1	0.821	0.816	0.833
SRES-3A	0.275	0.268	0.877	0.821	1	0.914	0.720
SRES-AAT	0.275	0.277	0.868	0.816	0.914	1	0.662
SRES-Drought (hazard-specific)	0.222	0.199	0.693	0.833	0.720	0.662	1

SM Table 3: Summary of model outputs comparing Hybrid-RIMA and SERS

	RIMA (objectively-evaluated resilience)				SRES (subjectively-evaluated resilience)			
	OLS	Fixed-effects	Fixed-effects (CRS)	Multi-level (Nested)	OLS	Fixed-effects	Fixed-effects (CRS)	Multi-level (Nested)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wealth index	0.256*** (0.008)	0.243*** (0.008)	0.243*** (0.006)	0.246*** (0.006)	0.151*** (0.023)	0.107*** (0.025)	0.107*** (0.030)	0.126*** (0.024)
Access to agricultural inputs	0.020* (0.008)	0.018* (0.008)	0.018 (0.009)	0.018** (0.006)	0.085*** (0.019)	0.083*** (0.020)	0.083*** (0.021)	0.084*** (0.022)
Access to credit	0.015*** (0.004)	0.019*** (0.004)	0.019*** (0.003)	0.018*** (0.003)	0.021* (0.011)	0.025* (0.011)	0.025* (0.012)	0.025* (0.011)
Crop disease affect (Base=Yes)	0.010*** (0.003)	0.005 (0.003)	0.005 (0.003)	0.006* (0.003)	0.017 (0.010)	0.030** (0.011)	0.030* (0.014)	0.026* (0.010)
Number of income sources	0.039*** (0.001)	0.039*** (0.001)	0.039*** (0.001)	0.039*** (0.001)	0.012** (0.004)	0.012** (0.004)	0.012* (0.005)	0.012** (0.004)
Diversity of food intake	-0.0002 (0.0005)	0.001 (0.0005)	0.001 (0.001)	0.0004 (0.0004)	0.010*** (0.002)	0.011*** (0.002)	0.011*** (0.002)	0.010*** (0.002)
log(Distance agri market+1)	-0.002 (0.002)	-0.001 (0.002)	-0.001 (0.001)	-0.001 (0.001)	0.002 (0.005)	-0.001 (0.006)	-0.001 (0.007)	0.001 (0.006)
Highest female education (yrs)	0.005*** (0.0003)	0.005*** (0.0003)	0.005*** (0.0004)	0.005*** (0.0003)	0.003* (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
Annual food consumption	0.0001* (0.00004)	0.00003 (0.00004)	0.00003 (0.00003)	0.00004 (0.00003)	0.0003* (0.0001)	0.0003* (0.0001)	0.0003 (0.0001)	0.0003* (0.0001)
Crop diversification	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	-0.0001 (0.0003)	-0.0001 (0.0003)	-0.0001 (0.0003)	-0.0001 (0.0003)
Age of household head	0.019*** (0.001)	0.022*** (0.001)	0.022*** (0.001)	0.021*** (0.001)	-0.003 (0.003)	-0.007 (0.004)	-0.007 (0.005)	-0.005 (0.003)
Education of household head (yrs)	0.006*** (0.0004)	0.005*** (0.0004)	0.005*** (0.0004)	0.006*** (0.0003)	-0.003* (0.001)	-0.003* (0.001)	-0.003* (0.001)	-0.003* (0.001)
Number of children	-0.005*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.005 (0.003)	-0.005 (0.003)	-0.005 (0.003)	-0.005 (0.003)
Flood affect (Base=Yes)	-0.006 (0.004)	-0.011* (0.005)	-0.011* (0.005)	-0.010* (0.005)	-0.023 (0.016)	-0.006 (0.018)	-0.006 (0.029)	-0.013 (0.018)
log(Distance livestock market+1)	-0.004* (0.002)	-0.004* (0.002)	-0.004 (0.002)	-0.004* (0.002)	-0.015** (0.005)	-0.022*** (0.006)	-0.022** (0.008)	-0.020** (0.006)
log(Distance hospital+1)	-0.005*** (0.001)	-0.004*** (0.001)	-0.004** (0.002)	-0.005*** (0.001)	-0.021*** (0.004)	-0.016*** (0.005)	-0.016* (0.007)	-0.019*** (0.005)
Coping Strategies Index (inv)	0.209*** (0.008)	0.205*** (0.008)	0.205*** (0.010)	0.206*** (0.006)	-0.042 (0.025)	-0.045 (0.026)	-0.045 (0.037)	-0.045* (0.023)
Farming livelihood (Base=Agro-pastoral)	-0.021*** (0.002)	-0.017*** (0.002)	-0.017*** (0.002)	-0.018*** (0.002)	-0.039*** (0.009)	-0.039*** (0.009)	-0.039*** (0.011)	-0.039*** (0.009)
Illness affect (Base=Yes)	-0.005 (0.003)	-0.005 (0.003)	-0.005 (0.003)	-0.005 (0.003)	-0.046*** (0.013)	-0.043*** (0.013)	-0.043** (0.016)	-0.044*** (0.013)
Drought affect (Base=Yes)	0.005 (0.004)	0.009* (0.004)	0.009 (0.004)	0.008* (0.004)	-0.051** (0.016)	-0.040* (0.017)	-0.040 (0.025)	-0.044** (0.015)
Gender household head (Base=Female)	-0.002 (0.027)	-0.004 (0.028)	-0.004 (0.017)	-0.004 (0.029)	-0.017 (0.238)	-0.069 (0.220)	-0.069 (0.147)	-0.048 (0.112)
Relationship status (Base=Divorced/separate)	-0.012 (0.027)	-0.011 (0.028)	-0.011 (0.017)	-0.011 (0.029)	-0.002 (0.238)	0.043 (0.220)	0.043 (0.144)	0.025 (0.112)
Constant	0.121*** (0.013)	0.108*** (0.018)		0.118*** (0.011)	0.499*** (0.037)	0.545*** (0.051)		0.518*** (0.041)
Observations	2,146	2,146	2,146	2,146	2,146	2,146	2,146	2,138
Sub-county FE	NO	YES	YES	-	NO	YES	YES	-

*Note: *p<0.05**p<0.01***p<0.001*

SM Figure 1: Coefficient plot comparing Hybrid-RIMA and SRES under different regression model specification



Notes: Dots represent beta coefficients; 95% confidence intervals are expressed as whiskers (coefficients with CIs that do not include 0 are considered significant at the p<0.05 level). Blue line = OLS model; Red line = District-level fixed effects model; Orange line = District-level fixed effects with clustered standard errors; Purple line= multi-level model

SM Table 4: Summary of model outputs comparing RIMA (original food-security variant) and SRES

	Original RIMA food-security variant				SRES 9C			
	OLS	Fixed-effects	Fixed-effects	Multi-level (Nested)	OLS	Fixed-effects	Fixed-effects (CRS)	Multi-level (Nested)
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Wealth index	0.016 (0.009)	0.028** (0.009)	0.028** (0.010)	0.024** (0.008)	0.151*** (0.023)	0.107*** (0.025)	0.107*** (0.030)	0.126*** (0.024)
Access to agricultural inputs	0.014* (0.007)	0.017* (0.008)	0.017 (0.011)	0.016* (0.008)	0.085*** (0.019)	0.083*** (0.020)	0.083*** (0.021)	0.084*** (0.022)
Access to credit	0.010* (0.004)	0.008 (0.004)	0.008 (0.006)	0.008* (0.004)	0.021* (0.011)	0.025* (0.011)	0.025* (0.012)	0.025* (0.011)
Crop disease affect (Base=Yes)	-0.013*** (0.004)	0.001 (0.004)	0.001 (0.005)	-0.003 (0.004)	0.017 (0.010)	0.030** (0.011)	0.030* (0.014)	0.026* (0.010)
Number of income sources	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)	0.012** (0.004)	0.012** (0.004)	0.012* (0.005)	0.012** (0.004)
Diversity of food intake	0.040*** (0.001)	0.039*** (0.001)	0.039*** (0.001)	0.039*** (0.001)	0.010*** (0.002)	0.011*** (0.002)	0.011*** (0.002)	0.010*** (0.002)
log(Distance agri market+1)	-0.003 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.002)	0.002 (0.005)	-0.001 (0.006)	-0.001 (0.007)	0.001 (0.006)
Highest female education (yrs)	0.001*** (0.0004)	0.002*** (0.0004)	0.002** (0.001)	0.002*** (0.0004)	0.003* (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
Annual food consumption	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.00004)	0.0003* (0.0001)	0.0003* (0.0001)	0.0003 (0.0001)	0.0003* (0.0001)
Crop diversification	0.0003** (0.0001)	0.0002* (0.0001)	0.0002* (0.0001)	0.0002* (0.0001)	-0.0001 (0.0003)	-0.0001 (0.0003)	-0.0001 (0.0003)	-0.0001 (0.0003)
Age of household head	0.004*** (0.001)	0.004** (0.001)	0.004** (0.002)	0.004*** (0.001)	-0.003 (0.003)	-0.007 (0.004)	-0.007 (0.005)	-0.005 (0.003)
Education of household head (yrs)	0.001 (0.0005)	0.001 (0.0005)	0.001 (0.0005)	0.001* (0.0004)	-0.003* (0.001)	-0.003* (0.001)	-0.003* (0.001)	-0.003* (0.001)
Number of children	-0.001 (0.001)	-0.0003 (0.001)	-0.0003 (0.001)	-0.0005 (0.001)	-0.005 (0.003)	-0.005 (0.003)	-0.005 (0.003)	-0.005 (0.003)
Flood affect (Base=Yes)	-0.007 (0.006)	-0.005 (0.006)	-0.005 (0.005)	-0.005 (0.006)	-0.023 (0.016)	-0.006 (0.018)	-0.006 (0.029)	-0.013 (0.018)
log(Distance livestock market+1)	-0.001 (0.002)	0.0001 (0.002)	0.0001 (0.003)	-0.001 (0.002)	-0.015** (0.005)	-0.022*** (0.006)	-0.022** (0.008)	-0.020** (0.006)
log(Distance hospital+1)	-0.0005 (0.001)	0.0002 (0.002)	0.0002 (0.003)	0.0002 (0.002)	-0.021*** (0.004)	-0.016*** (0.005)	-0.016* (0.007)	-0.019*** (0.005)
Coping Strategies Index (inv)	0.042*** (0.009)	0.047*** (0.009)	0.047*** (0.009)	0.045*** (0.008)	-0.042 (0.025)	-0.045 (0.026)	-0.045 (0.037)	-0.045* (0.023)
Farming livelihood (Base=Agro-pastoral)	-0.001 (0.003)	-0.004 (0.003)	-0.004 (0.004)	-0.004 (0.003)	-0.039*** (0.009)	-0.039*** (0.009)	-0.039*** (0.011)	-0.039*** (0.009)
Illness affect (Base=Yes)	-0.002 (0.004)	0.001 (0.004)	0.001 (0.005)	0.0003 (0.004)	-0.046*** (0.013)	-0.043*** (0.013)	-0.043** (0.016)	-0.044*** (0.013)
Drought affect (Base=Yes)	0.005 (0.005)	0.001 (0.005)	0.001 (0.006)	0.002 (0.005)	-0.051** (0.016)	-0.040* (0.017)	-0.040 (0.025)	-0.044** (0.015)
Gender household head (Base=Female)	-0.088 (0.095)	-0.057 (0.113)	-0.057 (0.074)	-0.065 (0.038)	-0.017 (0.238)	-0.069 (0.220)	-0.069 (0.147)	-0.048 (0.112)
Relationship status (Base=Divorced/separate)	0.079 (0.095)	0.046 (0.113)	0.046 (0.074)	0.055 (0.038)	-0.002 (0.238)	0.043 (0.220)	0.043 (0.144)	0.025 (0.112)
Constant	0.016 (0.009)	0.028** (0.009)	0.028** (0.010)	0.024** (0.008)	0.151*** (0.023)	0.107*** (0.025)	0.107*** (0.030)	0.126*** (0.024)
Observations	2,146	2,146	2,146	2,146	2,146	2,146	2,146	2,138
Sub-county FE	NO	YES	YES	-	NO	YES	YES	-

*Note: *p<0.05**p<0.01***p<0.001;*

SM Table 5: Summary of model outputs comparing RIMA and SRES-PCA variant

	RIMA (objectively-evaluated resilience)				SRES (subjectively-evaluated resilience)			
	OLS	Fixed-effects	Fixed-effects (CRS)	Multi- (Nested)	OLS	Fixed-effects	Fixed-effects (CRS)	Nested Multi-level
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Wealth index	0.016 (0.009)	0.028** (0.009)	0.028** (0.010)	0.024** (0.008)	0.128*** (0.021)	0.097*** (0.022)	0.097*** (0.026)	0.108*** (0.021)
Access to agricultural inputs	0.014* (0.007)	0.017* (0.008)	0.017 (0.011)	0.016* (0.008)	0.081*** (0.014)	0.082*** (0.016)	0.082*** (0.017)	0.082*** (0.019)
Access to credit	0.010* (0.004)	0.008 (0.004)	0.008 (0.006)	0.008* (0.004)	0.002 (0.010)	0.009 (0.010)	0.009 (0.009)	0.007 (0.010)
Crop disease affect (Base=Yes)	-0.013*** (0.004)	0.001 (0.004)	0.001 (0.005)	-0.003 (0.004)	0.018* (0.009)	0.040*** (0.010)	0.040** (0.013)	0.035*** (0.009)
Number of income sources	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)	0.013*** (0.004)	0.013*** (0.004)	0.013** (0.004)	0.013*** (0.004)
Diversity of food intake	0.040*** (0.001)	0.039*** (0.001)	0.039*** (0.001)	0.039*** (0.001)	0.009*** (0.001)	0.010*** (0.001)	0.010*** (0.002)	0.009*** (0.001)
log(Distance agri market+1)	-0.003 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.002)	0.0002 (0.005)	-0.005 (0.005)	-0.005 (0.007)	-0.003 (0.005)
Highest female education	0.001*** (0.0004)	0.002*** (0.0004)	0.002** (0.001)	0.002*** (0.0004)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Annual food consumption	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.00004)	0.0003** (0.0001)	0.0003* (0.0001)	0.0003 (0.0001)	0.0003* (0.0001)
Crop diversification	0.0003** (0.0001)	0.0002* (0.0001)	0.0002* (0.0001)	0.0002* (0.0001)	0.00004 (0.0002)	-0.00004 (0.0002)	-0.00004 (0.0002)	-0.00003 (0.0002)
Age of household head	0.004*** (0.001)	0.004** (0.001)	0.004** (0.002)	0.004*** (0.001)	-0.008** (0.003)	-0.009** (0.003)	-0.009* (0.004)	-0.008** (0.003)
Education of household head	0.001 (0.0005)	0.001 (0.0005)	0.001 (0.0005)	0.001* (0.0004)	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)
Number of children	-0.001 (0.001)	-0.0003 (0.001)	-0.0003 (0.001)	-0.0005 (0.001)	-0.004 (0.002)	-0.004 (0.002)	-0.004 (0.003)	-0.004 (0.002)
Flood affect (Base=Yes)	-0.007 (0.006)	-0.005 (0.006)	-0.005 (0.005)	-0.005 (0.006)	-0.019 (0.013)	-0.021 (0.015)	-0.021 (0.019)	-0.020 (0.015)
log(Distance livestock market+1)	-0.001 (0.002)	0.0001 (0.002)	0.0001 (0.003)	-0.001 (0.002)	-0.015** (0.005)	-0.019*** (0.005)	-0.019* (0.008)	-0.018*** (0.005)
log(Distance hospital+1)	-0.0005 (0.001)	0.0002 (0.002)	0.0002 (0.003)	0.0002 (0.002)	-0.014*** (0.004)	-0.012** (0.004)	-0.012* (0.005)	-0.013** (0.004)
Coping Strategies Index (inv)	0.042*** (0.009)	0.047*** (0.009)	0.047*** (0.009)	0.045*** (0.008)	-0.005 (0.023)	-0.014 (0.023)	-0.014 (0.031)	-0.012 (0.019)
Farming livelihood (Base=Agro-pastoral)	-0.001 (0.003)	-0.004 (0.003)	-0.004 (0.004)	-0.004 (0.003)	-0.032*** (0.008)	-0.031*** (0.008)	-0.031*** (0.009)	-0.031*** (0.008)
Illness affect (Base=Yes)	-0.002 (0.004)	0.001 (0.004)	0.001 (0.005)	0.0003 (0.004)	-0.033** (0.011)	-0.027* (0.011)	-0.027* (0.012)	-0.028** (0.011)
Drought affect (Base=Yes)	0.005 (0.005)	0.001 (0.005)	0.001 (0.006)	0.002 (0.005)	-0.053*** (0.014)	-0.040** (0.015)	-0.040* (0.020)	-0.044*** (0.013)
Gender household head (Base=Female)	-0.088 (0.095)	-0.057 (0.113)	-0.057 (0.074)	-0.065 (0.038)	0.052 (0.220)	0.020 (0.196)	0.020 (0.131)	0.033 (0.095)
Relationship status (Base=Divorced/separate)	0.079 (0.095)	0.046 (0.113)	0.046 (0.074)	0.055 (0.038)	-0.066 (0.220)	-0.040 (0.196)	-0.040 (0.129)	-0.051 (0.095)
Constant	0.016 (0.009)	0.028** (0.009)	0.028** (0.010)	0.024** (0.008)	0.128*** (0.021)	0.097*** (0.022)	0.097*** (0.026)	0.108*** (0.021)
Observations	2,146	2,146	2,146	2,146	2,146	2,146	2,146	2,138
Sub-county FE	NO	YES	YES	-	NO	YES	YES	-

Note: *p<0.05**p<0.01***p<0.001

SM Table 6: Comparison of variants of the SRES approach

	SRES-9C	SRES-3A	SRES-AAT	SRES-9A (excluding same response)
	(25)	(26)	(27)	(28)
Wealth index	0.107*** (0.030)	0.134*** (0.028)	0.126*** (0.027)	0.095** (0.030)
Access to agricultural inputs	0.083*** (0.021)	0.084** (0.026)	0.102*** (0.026)	0.069*** (0.018)
Access to credit	0.025* (0.012)	0.015 (0.013)	0.029 (0.016)	0.028* (0.012)
Crop disease affect (Base=Yes)	0.030* (0.014)	0.019 (0.016)	0.010 (0.015)	0.030* (0.014)
Number of income sources	0.012* (0.005)	0.013** (0.005)	0.015** (0.006)	0.010* (0.004)
Diversity of food intake	0.011*** (0.002)	0.013*** (0.002)	0.012*** (0.002)	0.011*** (0.002)
log(Distance agri market+1)	-0.001 (0.007)	-0.003 (0.008)	-0.0004 (0.009)	-0.001 (0.007)
Highest female education (yrs)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)
Annual food consumption	0.0003 (0.0001)	0.0001 (0.0002)	0.0003 (0.0002)	0.0003* (0.0001)
Crop diversification	-0.0001 (0.0003)	0.0001 (0.0003)	-0.0003 (0.0003)	-0.00003 (0.0003)
Age of household head	-0.007 (0.005)	-0.007 (0.005)	-0.004 (0.006)	-0.006 (0.005)
Education of household head (yrs)	-0.003* (0.001)	-0.003 (0.002)	-0.003 (0.002)	-0.003* (0.001)
Number of children	-0.005 (0.003)	-0.005 (0.003)	-0.003 (0.004)	-0.005 (0.003)
Flood affect (Base=Yes)	-0.006 (0.029)	-0.031 (0.021)	0.003 (0.024)	-0.006 (0.030)
log(Distance livestock market+1)	-0.022** (0.008)	-0.019* (0.008)	-0.018* (0.009)	-0.022** (0.008)
log(Distance hospital+1)	-0.016* (0.007)	-0.017** (0.006)	-0.019** (0.007)	-0.016* (0.007)
Coping Strategies Index (inv)	-0.045 (0.037)	-0.028 (0.040)	-0.041 (0.042)	-0.050 (0.037)
Farming livelihood (Base=Agro-pastoral)	-0.039*** (0.011)	-0.046** (0.014)	-0.053*** (0.013)	-0.033** (0.011)
Illness affect (Base=Yes)	-0.043** (0.016)	-0.025 (0.017)	-0.028 (0.018)	-0.040* (0.016)
Drought affect (Base=Yes)	-0.040 (0.025)	-0.041 (0.023)	-0.055* (0.026)	-0.040 (0.024)
Gender household head (Base=Female)	-0.069 (0.147)	-0.015 (0.171)	-0.015 (0.149)	-0.074 (0.148)
Relationship status (Base=Divorced/separate)	0.043 (0.144)	-0.009 (0.170)	-0.021 (0.148)	0.055 (0.145)
Observations	2,146	2,146	2,146	2,146
Sub-county FE	NO	YES	YES	YES

*Note: *p<0.05**p<0.01***p<0.001;*

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