London School of Economics and Political Science

Essays on Resilience Measurement

Lindsey Jones

A thesis submitted to the Department of Geography and the Environment of the London School of Economics for the degree of Doctor of Philosophy

February 2020

Declaration

I certify that this thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I confirm that a version of Chapter 1 is published in Wiley Interdisciplinary Reviews Climate Change (WIRES-CC), Volume 10, Issue 1 January/February 2018.

I confirm that Chapter 2 was co-authored with Dr. Marco D'Errico (United Nations Food and Agriculture Organisation). Marco supported data collection, provided inputs into the design of the study and calculated the RIMA module. I led the overall study design, devised the SERS module, carried out all statistical analyses and drafted the paper. A version of this chapter is published in World Development, Volume 124, December 2019. It also features as a Grantham Research Institute on Climate Change and the Environment Working Paper (No. 303, ISSN 2515-5717).

I confirm that Chapter 3 was co-authored with Dr. Paola Ballon (University of Oxford). Paola helped with choice of statistical methods and data verification. I led the overall study design and collection of survey data, carried out all statistical analyses and wrote the paper. A version of this chapter has been accepted and is currently in press in Global Environmental Change. Parts also feature in two Building Resilience and Adaptation to Climate Extremes and Disasters (BRACED) working papers: 'New methods in resilience measurement' (2018) and 'How does resilience change over time' (2018).

I declare that my thesis consists of approximately 71,000 words.

Lindsey Jones
London, February 2020

Abstract

Robust measurement is key to the design and targeting of resilience-building interventions. Yet, conventional approaches to resilience measurement are often ill-suited to the needs of development and humanitarian stakeholders, proving costly, time-consuming and difficult to coordinate.

In this thesis I explore the use, validity and viability of an alternative suite of approaches: subjective measures of resilience. I start by clarifying the conceptual distinctions between subjectivity and objectivity as they relate to resilience measurement, before introducing a continuum that highlights the strengths and weaknesses of different types of approaches. I then develop a new perception-based measure, coined the Subjectively self-Evaluated Resilience Score (SERS). Using a large household survey in Northern Uganda, I provide like-for-like comparisons between SERS and a conventional objective approach to resilience measurement. While I show that the two measures are moderately correlated, they differ notably in associations with key socio-economic traits.

In order to further probe the validity of subjective measures, I examine whether SERS is sensitive to external shocks. Using mobile phones to conduct remote interviews I assemble a novel high-frequency panel survey on resilience. Here I reveal how perceived levels of resilience fluctuate in the aftermath of seasonal flooding in Eastern Myanmar: dropping sharply in the first few months, before slowly converging over the course of a year. I also compare the impact of flood exposure across different socio-economic groups, revealing how female-headed households are hardest hit. Lastly, using the same site in Myanmar, I look more closely at the temporal dynamics of resilience. Insights from an extended panel provide quantitative evidence of intra-annual variation in levels of resilience. Here I find consistent non-linear associations between subjectively-evaluated scores and changes in seasonality and weather. Findings also point to potential resilience thresholds and tipping points. Weighed together, these results: challenge core assumptions in the resilience literature; highlight the potential of subjective measures; and point to the need for greater diversity of resilience evidence.

Acknowledgements

Ironically for a researcher of all things resilience, a thesis turns out to be a microcosm of unexpected shocks, persistent turmoil and seemingly insurmountable obstacles. Not to mention the continual tests of patience, ego and willpower.

From the lofty highs of Hpa An field visits, to the cavernous lows of PhD-room construction work, I drew on the support of so many to make this happen.

To those eager to work with me, share crazy ideas and embark on untested projects. Thank you to my collaborators and research partners. To Emma, Htun Htun, Jeremy, Johannes, Marco, Paola and all those at ODI, BRACED and FAO. None of this would've been possible without you.

To those able to tame my rambling thoughts. Thank you to my supervisor, Declan, for giving me the flexibility and trust to continually disappear; re-emerging (occasionally) with unformed ideas and overly-ambitious aims. Your guidance is invaluable, and you serve as the perfect role model for policy-relevant research.

To those always there to offer a smile, joke and laugh along the way. Thank you to the irrepressible PhD gang that stuck it through with me. Andreas, David, Eduardo, Elisabetta, Lars, Louise, Margarida, Marta, Matt, Mook, Yohan and countless others.

To those forever there to pick me off the floor (and take me down from the ceiling). Thank you to the other Lindsey. You've been there whenever I've needed it, and believe in me more so than I do. I can't wait for adventures to come.

To those there to inspire me. Thank you to my family and parents. You've provided me with inspiration and guidance from the very start. I'm forever grateful.

Table of contents

List of Figures

List of Tables

Introduction

Measuring resilience is crucial to understanding it. Yet, while the international development community commits ever-larger sums in support of resilience-building, existing measurement tools are not up to the task. In this thesis I examine the potential of a largely untested approach: subjective measures of household resilience. Perception-based methods offer novel ways of feeding people's knowledge of their own resilience into the measurement process itself. They allow for local insights to be factored in, ground-truthing measures of resilience from the perspective of those directly at risk.

Broadly speaking, resilience measurement can be classified into two categories. Objective measures are those reliant on external definitions or evaluations of resilience. By their very nature they are (largely) devoid of judgements from the subjects in question. Objective approaches to resilience measurement borrow heavily from tools used to measure related socio-economic traits such as poverty, livelihoods and food security. They typically make use of large lists of proxy indicators that can be borrowed from conventional household survey datasets (Schipper and Langston 2015). As such, objective measures remain the mainstay of the resilience measurement landscape.

Subjective forms of resilience measurement take an altogether different approach. Rather than relying on external observations, they focus on people's insights into their own resilience. Subjective measures solicit the perceptions, preferences and judgements of those being measured themselves. They can be readily quantified using conventional psychometric approaches and compared alongside (or integrated within) traditional objective approaches to resilience measurement.

This thesis is devoted to exploring the nature, validity and viability of this latter approach. It adds weight to a growing body of evidence seeking to develop and test subjective measures of resilience as an alternative to more conventional objective approaches. In doing so, I structure this thesis in accordance with a series of deductive steps – moving from theory development to data collection and analysis.

More specifically, I aim to:

i) Clarify conceptual distinctions between subjective and objective approaches to resilience measurement;
ii) Compare outcomes from perception-based tools with those of existing objective measures; and
iii) Gather quantitative insights into the temporal dynamics of resilience, as well as potential associations with wider environmental factors

Insights into these research aims are provided through four research chapters that form the heart of this thesis. Each chapter is written as a stand-alone paper, meaning that some degree of overlap in framing and background may inevitably result. Below I highlight the contributions of the four chapters in seeking to address the main research aims.

In Chapter 1 I map out the conceptual boundaries between subjectivity and objectivity as applied to resilience measurement. While these distinctions are discussed extensively in the related fields of wellbeing (Diener et al. 2006; Dolan and Metcalfe 2012; OECD 2013), deprivation (Mishra and Carlten 2015; Muffels 2014), health (Etherton et al 2014) and risk (Mills et al. 2016; Wachinger et al. 2013), their relevance to resilience measurement has been largely overlooked. In clarifying the relationship between the two, I add to the resilience knowledge base by presenting a novel continuum that distinguishes between objective and subjective aspects of resilience measurement.

The objectivity-subjectivity continuum differentiates two key traits. The first is how resilience is defined, i.e. whether defined externally or via the subject(s) in question. The second is how resilience is evaluated, i.e. whether evaluated by external observation or using the subject's own judgement. By visualising the continuum, four quadrants are easily identifiable. Each quadrant constitutes a distinct category of measurement. I then map out a range of commonly used measurement tools (17 in total) against the continuum, pointing to clusters and gaps in the evidence base. I draw on examples from these tools to highlight the strengths and weaknesses of the four measurement categories.

Overall, I find that the majority of tools fall into the category of 'objectively-defined & objectively-evaluated'. Reassuringly, a number of emerging examples of 'objectively-defined & subjectively-evaluated' tools have emerged. These help to inform the creation of a new subjective module in the chapters that follow. However, I also point out that few existing measures can be considered as subjectively-defined (irrespective of how they are evaluated). While I outline some of the methodological reasons behind this shortfall, I underscore their potential for future measurement approaches.

In Chapter 2 I move from a conceptual comparison to an empirical one. Here I look to compare resilience scores between subjectively- and objectively-evaluated approaches to measurement. To do so I carry out a large household survey in Northern Uganda. The initiative comprises responses from 2,380 households and is coordinated alongside the United Nations Food and Agriculture Organisation (FAO). Together with a co-author, Marco D'Errico, we calculate resilience scores for each household based on a conventional objectively-evaluated measure: FAO's Resilience Index Measurement Analysis (RIMA) (FAO 2016). RIMA is widely used by development practitioners (FSIN 2014a; D'Errico & Giuseppe 2014; D'Errico et al. 2017) and consists of a range of socio-economic proxy variables that are fed into a structural equation model. At the same time, we also evaluate each household using a subjective approach.

Here a new survey module is devised: the Subjectively self-Evaluated Resilience Score (SERS). SERS builds on earlier versions of a similar tool trialled in Tanzania and Kenya (see Jones and Samman 2016). The SERS module consists of a self-evaluated questionnaire comprising nine resilience-related statements. Each statement relates to a pre-defined capacity or capital chosen from an extensive review of available literature (hence why the approach falls under the category of 'objectively-defined & subjectively-evaluated' under the continuum in Chapter 1). Respondents are asked to rate levels of agreement with all nine statements, ranging from strongly agree to strongly disagree. Answers are then numerically converted to form an overall score: one that can be directly compared with RIMA.

Using scores from RIMA and SERS we provide like-for-like comparisons of objective and subjective measures for the first time. Our findings reveal a modest correlation between the two measures. We show how both measures showcase similar associations with a number of socio-economic traits – such as wealth, income diversity and livelihood type. However, clear differences are also noticeable. For a start, many factors commonly linked with resilience have opposing associations with the two resilience measures – including coping strategies, levels of education and exposure to prior shocks. In addition, we examine the properties of the SERS module itself, revealing how different characterisations of resilience result in similar resilience outcomes.

Findings from Chapter 2 point to a number of important implications for how resilience is understood and measured. Firstly, they suggest that assumed drivers of resilience differ depending on whether evaluation is carried out internally (via a person's own judgement) or externally (via expert judgement). They point to the need for evaluators to consider a diversity of knowledge sources, and seek a stronger and more transparent evidence base in choosing relevant indicators. These findings are further underscored by the fact that, when it comes to indicator selection, some toolkits place heavier emphasis on data availability than theoretical and ground-truthed reasoning (Schipper and Langston 2015; Ruszczyk 2019).

In Chapter 3 I further probe the validity of subjectively-evaluated measures by examining sensitivity to external shocks. In particular, I track changes in SERS in the aftermath of heavy flooding for the district of Hpa An, Eastern Myanmar. In doing so I collect a unique high-frequency panel survey on household resilience. Crucially, the brevity of the SERS module allows for resilience to be tracked in new ways, including administration via mobile phone. After setting up a call centre in the city of Yangon, together with the Building Resilience and Adaptation to Climate Extremes and Disasters (BRACED) programme in Myanmar, a series of post-disaster phone surveys were carried out with

1,072 households. Surveys took place every six-to-eight weeks over a one-year period starting in June 2017, with over 9,500 observations gathered during the course of the panel.

Findings reveal how levels of household resilience drop sharply in the aftermath of seasonal flooding. Scores rebound 3-4 months later, before slowly converging over time. Together with a co-author, Paola Ballon, we look at the effects of flood exposure on resilience outcomes by comparing directly and indirectly affected households using a difference-in-differences approach coupled with a matching procedure. Here we show how households directly exposed to flooding have significantly lower scores over time. In addition, the dataset allows for comparisons of different socio-economic groups. By calculating a 'resilience-over-time' score (an integral of resilience scores over the course of the total survey period) we reveal how, amongst others, female-headed households are hit hardest in the aftermath of the flooding.

Together, these insights point to the viability and flexibility of the SERS module. They suggest that subjective-evaluations are responsive to external stimuli (as one might expect), and show consistent plausible patterns related to exposure and recovery over time. Crucially, responses display heterogeneity across social groups and time. They showcase the potential of using SERS as a means of tracking the status of different socio-economic groups in the aftermath of shock events – a property of considerable use to development and humanitarian actors if shown to be robust.

In Chapter 4 I take the analysis one step further by looking at links between intra-annual changes in subjectively-evaluated resilience and wider environmental factors like seasonality and weather. To date, quantitative evidence of how levels of resilience change over time is limited. There are two primary reasons for this. Firstly, the vast majority of resilience assessments take place as snap-shots: one-off surveys carried out at a single point in time (Schipper and Langston 2015). In a handful of occasions repeated measures of resilience have been taken, often comparing scores between baseline and end-line periods to evaluate the impact of a resilience-building intervention (Kim & Marcouillier 2016; Cisse & Barret 2015; D'Errico & Di Giuseppe 2016). Yet, these offer little insight into intra-annual dynamics as surveys are often conducted years apart. A second reason is that many resilience measurement tools are ill-equipped to pick up on short-term changes. Most rely heavily on immutable proxy indicators (Schipper and Langston 2015): ones that seldom change (or evolve slowly over time)

Despite this, there are good theoretical reasons to believe that a household's ability to deal with risk fluctuates on short-term timescales. For a start, related literatures on vulnerability, sustainable livelihoods and food security have long histories documenting the influence of seasonality and intra-seasonal dynamics on livelihood outcomes (Chambers et al. 1981; Longhurst et al. 1986; Deveroux et al. 2013; Rohwerder 2016; Apanovich & Mazur 2018). Moreover, qualitative insights highlight how resilience-related capacities are influenced by short-term changes in local environment and socio-economic conditions (Raju 2019). However, little quantitative evidence is available to investigate these claims.

To shed light on this evidence gap I return to the Myanmar case study. More specifically, I look at whether changes in subjective-evaluated resilience are linked with intra-annual fluctuations in seasonality and weather anomalies. Here I extend the Myanmar panel to include 10 survey waves. This results in an augmented panel that spans a 17-month period. By employing a series of regression models I show how SERS scores differ significantly across the region's wet, dry and hot seasons. I then match timestamps from each household survey with daily ground- and satellite-based weather observations for Hpa An. By comparing information from these datasets I am able to examine the relationship between resilience scores and changes in weather conditions (both in absolute terms as well as anomalies relative to the historical record).

Findings from the analysis reveal clear relationships between resilience and shifts in key weather parameters – both across and within seasons. By comparing the weather during the time of interview with historical records I also show how periods with above and below average weather conditions are similarly linked with changes in SERS. Most strikingly, a large number of these relationships are non-linear, with most following a quadratic trend. Indeed, some of these associations have sharp cut-offs, potentially suggestive of resilience thresholds and tipping points. These results are broadly replicated by data from a secondary site in Mudon, 60 kilometers South of Hpa An.

Results from Chapter 4 add considerably to our understanding of how levels of resilience (and the capacities that contribute to it) change over time. They also have importantly implications for policy and practice. Firstly, they require development actors to think carefully about how interventions are monitored and evaluated. For example, an instance where baseline information is collected during a different season to mid- or end-line assessments may risk erroneously attributing resilience gains (or losses) to the project rather than potential seasonal shifts. They also highlight the need for development actors to pay closer attention to shorter-term dynamics of resilience in the design of resilience-related interventions. This may mean tailoring targeted resilience-building activities to different seasonal needs – such as seasonal initiatives employed under various social protection programmes (Hagen-Zanker et al. 2017).

Finally, in Chapter 5 I weigh up the overall contributions of this thesis to the resilience evidence base. I also point out how each chapter offers new insights into our understanding of resilience and its measurement. More specifically, Chapter 1 presents the theoretical distinctions between objective and subjective approaches. It clarifies many of the conceptual ambiguities found in the mislabelling of measurement tools, and significantly extends the early framework presented by Maxwell et al. (2015) and more recent theoretical work by Clare et al (2017), Béné et al. (2016b) and Béné et al. (2019). Chapter 2 contributes a new method for subjectively-evaluating household resilience. It provides the first direct comparison of objective and subjective measures, questioning many of the assumptions made in selecting conventional resilience indicators. Chapters

3 and 4 provide unique quantitative insights into the temporal dynamics of resilience. Here subjective-evaluations of resilience are shown to be responsive to external stressors (in this case seasonal flooding). They also exhibit clear non-linear associations with seasonality and weather. Both properties provide detailed insights into how resilience fluctuates on short-term timescales and encourage development and humanitarian actors to tailor resilience-building interventions accordingly.

Not only do findings from this thesis highlight the potential for subjective measures to gather robust information about risk and resilience, they unlock the novelty of mobile phones for use in data collection. The combination of these two tools offers remote, low-cost and near-real time insights into how resilience manifests on the ground. These traits are particularly relevant in post-disaster environments: contexts where it may be too costly, unsafe or impractical to carry out traditional face-to-face resilience assessments. Above all, this thesis showcases the need for further innovations in resilience measurement. Doing so is crucial to unlocking fresh insights into our understanding of resilience and how it should be measured; helping to guide the design of development and humanitarian initiatives aimed at protecting lives and livelihoods in multi-risk environments.

Chapter 1

Comparing subjective and objective approaches to resilience measurement

Lindsey Jones

Resilience measurement has a crucial role to play in improving our understanding of how people and societies respond to risk. It can also support development practitioners in tracking the effectiveness of resilience-building interventions over time. To date, the majority of assessment tools focus on objective approaches to resilience measurement. Broadly speaking, these relate to approaches that solicit little, if any, judgement on behalf of the subject in question. More recently, subjective measures have been proposed. These take a contrasting epistemological view, relying on people's self-evaluations of their own capacity to deal with risk. Subjective approaches offer some promise in complementing objective methods, including: factoring in people's own knowledge of resilience and what contributes to it; nuanced contextualisation; and the potential to reduce survey length and fatigue. Yet, considerable confusion still exists in how subjectivity and objectivity are understood in the context of resilience measurement. Little is also known about the merits and limitations of different approaches. Here, I clarify the conceptual and practical relationships between objective and subjective forms of resilience measurement, aiming to provide practical guidance in distinguishing between them. In reviewing existing toolkits, I propose a subjectivity-objectivity continuum that groups measurement approaches according to two core tenets: i) how resilience is defined; and ii) how resilience is evaluated. I then use the continuum to explore the strengthens and weaknesses of different types of toolkits, allowing comparison across each. Finally, I highlight important knowledge gaps and avenues for future research.

1.1. INTRODUCTION

Ensuring that people and communities are resilient to climate variability and change is a key development priority. It is enshrined in flagship global accords such as the United Nation's Paris Agreement (UN 2015a) and Agenda 2030 (UN 2015b). This rise in policy interest has inevitably led to calls to identify robust ways of measuring resilience across scales. The rationale is that accurate measurement can support more effective and targeted resilience-building interventions on the ground. Accordingly, myriad different frameworks and tools have sprouted. Despite this diversity, standardised approaches to resilience measurement can largely be broken down into two categories: objective and subjective evaluations (Maxwell et al. 2015; Claire et al. 2017; Jones and Tanner 2017).

Objective approaches commonly refer to aspects of measurement that are independent of the subject's judgement. With regards to resilience, this usually relates to approaches that use characterisations of resilience that are externally defined (i.e. defined by the evaluator rather than the people or communities being assessed). It also refers to approaches where measurement takes place via external observation, or use of questions that solicit little (if any) judgement on the part of subjects. Objective approaches to resilience measurement remain the norm across both research and practice (Schipper and Langston 2015; MEL-CoP 2016). As such, they have a large influence on our understanding of how societies respond to climate variability and change.

More recently, subjective methods of resilience measurement have been advocated (Maxwell et al. 2015; Jones and Tanner 2017; Claire et al 2017; Béné et al. 2016a). These take a very different approach, placing considerable value in people's knowledge of their own resilience and the factors that contribute to it. Subjective approaches actively include perspectives and judgements of the subject in question. Subjective tools can relate to approaches that make use of people's perceptions of: what resilience means to them; what factors contribute to their own resilience; as well as self-evaluations of their capacities to respond to climate risk. At their core, they seek to remove the influence of outside framings of resilience, as well as limiting comparisons with pre-determined indicators (such as those based on resilience literature or expert-elicitation).

Despite a growing number of studies showing interest in subjective methods, common findings have yet to be synthesised within the academic literature. In addition, considerable confusion still exists amongst researchers in distinguishing between subjectivity and objectivity. Such clarity is important not only in influencing the way in which researchers interpret their own work, but may point to new methods that can be used alongside existing resilience tools. It is here where this article seeks to add value.

This paper synthesises the state of existing literature relating to subjective and objective approaches to measuring resilience. It clarifies the conceptual distinctions between the two, aiming to support evaluators and practitioners in classifying their own (and other's) work. This is done by isolating several common toolkits to illustrate and present a novel objective-subjective continuum, upon which resilience toolkits can be mapped. The paper also describes the merits and limitations of subjective and objective approaches. It provides researchers with greater clarity on the inevitable trade-offs and assumptions involved in adopting different measurement tools. Doing so is important to improving our understanding of resilience and the factors that contribute to it. It is also crucial for efforts to more effectively monitor and evaluate resilience-building interventions. Lastly, critical knowledge gaps and avenues for future research are highlighted, seeking to advance the development a burgeoning and policy-relevant area of climate and development research.

1.2. THE STATE OF RESILIENCE MEASUREMENT

Before delving into the nuances of subjectivity and objectivity, it is important to clarify the definition of resilience and its conceptual evolution. Resilience has long conceptual histories spanning multiple academic disciplines (Alexander 2013). More recently, the term has found prominence within the ecological and social sciences. Here it is used to characterise the complex dynamics between linked socio-ecological systems in responding to disturbance and change (Carpenter et al., 2001; Folke et al., 2010). Despite – and perhaps owing to – its use across a range of broad disciplines, resilience has a chequered definitional history.

While references to resilience can be found from engineering and psychology, to art and literature (Alexander 2013), its application within the social sciences largely stems from its adoption within the ecology literature. Here resilience has historically been linked with the capacity to absorb change and disturbance in order to maintain core functions (Holling 1973; Odum 1985; Walker et al. 1981). The translation of resilience into social systems also brought with it greater recognition of a system's ability to adapt and change its core structure and functions (Schipper and Langston 2015). In many ways, this is where much of the conceptual ambiguity stems. For one, different perspectives on what resilience constitutes, and its proliferation across a range of academic and political contexts make settling on a standardised definition tricky, if not futile:

> "*It is clear that resilience thinking describes important attributes of ecosystems, of materials, and of human beings, that is, the ability to cope with, and recover after, disturbance, shocks, and stress. However, with popularity comes the risk of blurring and diluting the meaning.*" (Olsson et al. 2015:2).

Indeed, in some cases, authors argue that a complete transformation of a system may constitute, and be a necessary component of, resilience (Aldunce 2015; Kates & Travis 2012; Béné et al 2012). Evidence of the evolution of resilience over time can be seen in the changing nature of resilience within successive Intergovernmental Panel on Climate Change (IPCC) Assessment Reports (Table 1). While the Third Assessment describes a simple yet clearly defined concept that relates to maintaining the same system properties, the Fourth and Fifth Assessments have a much denser and all-encompassing definition. Intriguingly, these feature references to the capacity to adapt (AR4) as well as transform (AR5) – in apparent contradiction to the earlier definitions in the Third Assessment. By way of comparison, the IPCC's definition for adaptive capacity has seen little change over the same time period.

Table 1: The definitional evolution of 'Resilience' and 'Adaptive capacity' in successive IPCC assessment reports

Term	TAR (2001)	AR4 (2007)	AR5 (2014)
Resilience	"Amount of change a system can undergo without changing state."	"The ability of a social or ecological system to absorb disturbances while retaining the same basic structure and ways of functioning, the capacity for self-organisation, and the capacity to adapt to stress and change."	"The capacity of social, economic, and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganizing in ways that maintain their essential function, identity, and structure, while also maintaining the capacity for adaptation, learning, and transformation."
Adaptive Capacity	"The ability of a system to adjust to climate change (including climate variability and extremes) to moderate potential damages, to take advantage of opportunities, or to cope with the consequences."	"The ability of a system to adjust to climate change (including climate variability and extremes) to moderate potential damages, to take advantage of opportunities, or to cope with the consequences."	"The ability of systems, institutions, humans, and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences."

Adapted from Jones et al (2017) using sources from IPCC (2001); IPCC (2007); Agard et al. (2014)

Needless to say, the definitional inconsistencies described are a considerable challenge to resilience measurement (see Nelson 2010 and McEvoy et al. 2013 for comprehensive descriptions). Despite this, a wide range of frameworks and toolkits have emerged in recent years aimed at both research and policy making communities alike (Schipper and Langston 2015).

1.3. SUBJECTIVITY AND OBJECTIVITY IN RELATION TO RESILIENCE MEASUREMENT

Armed with a clearer sense of the concept of resilience and its evolution, I now delve into the distinctions between objectivity and subjectivity as applied to measurement. Here, I refer to measurement as processes taken to directly or indirectly measure a system's resilience. In particularly, I focus this analysis on the resilience of households and individuals, as units that are of keen relevance to humanitarian and development actors (FSIN 2014a; Schipper and Langston 2015; Bahadur and Pichon 2017). Measurement can be carried out for a range of purposes including improved understanding of the properties of resilience and factors that cause it. It can also be used as situational analyses to determine the extent of a person or community's resilience (FSIN 2014b). I also include efforts aimed at Monitoring and Evaluation (M&E), a subset of measurement that seeks to evaluate the impact of projects and interventions.

1.3.1. Objective modes of resilience measurement

Broadly speaking, objective methods can be thought of as independent of judgements arising from the subjects being observed (Cohen et al. 2002). In the context of resilience measurement, objectivity can relate to a wide range of steps – from choices in definitions and frameworks, to how data is collected and used in quantifying resilience. For example, most measurement toolkits rely on frameworks for resilience that are based on expert-elicitation or wider academic literature (Schipper & Langston 2015). Such approaches are largely objective, in the sense that resilience is externally defined: those being measured have little or no say in determining what constitutes resilience.

Objectivity also extends to the process of direct measurement. For example, many measurement toolkits include household or livelihood assets as one of the many proxies that are fed into a resilience index (FAO 2016; Frankenberger et al. 2013; Mayunga 2007). The assumption here is that higher levels of asset-wealth or diversity are associated with higher resilience (Adger 2000; Osbhar 2008). Accordingly, enumerators are often tasked with directly observing the subject's household – such as reporting on the type of building material used or counting household assets. This can be seen as objective, in that measurement involves external observation on the part of the enumerator (and is independent of the subject's own judgement).

Distinctions are somewhat blurred when it comes to the use of survey questions: the workhorse of most resilience measurement toolkits. Given that questions are posed directly to the subject, households surveys generally constitute self-evaluations. Yet, the degree to which they are subjective or objective depends on the nature of the question(s) being asked. Those that solicit the subject's perceptions, preferences and judgements can viably be classed as subjective. Yet, for the most part, existing resilience measures rely on survey questions that are void of their opinion. For example, use of a survey question such as 'Has the head of household completed primary-level education' requires little subjective judgement on the part of the respondent. Moreover, provided the question is understood similarly by all, it should result in similar answers no matter which adult in the household is asked. Admittedly, however, some room for interpretation and judgement is always present – an issue I return to later.

1.3.2. Subjective modes of measurement

While objective approaches to resilience measurement remain the norm, subjective modes have increasingly been advocated (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 take a contrasting epistemological view to objective methods. They challenge the notion that experts are best placed to evaluate other people's lives and have a better understanding of the factors that contribute to people's own resilience. Rather than relying on external judgement, subjective tools consider the individuals in question to understand their circumstances (Nguyen and James 2013). At its simplest, subjective approaches relate to an individual's cognitive and affective self-evaluation of the capabilities and capacities of their household, community or any other social system in responding to risk (Jones and Tanner 2015).

Subjective assessments rely heavily on the measurement of perceptions, judgements and preferences (Maxwell et al. 2015). They draw heavily on the conceptual and methodological advances made in related fields such as measurement of risk perception (Mills et al. 2016), psychological resilience (Connor and Davidson 2003) and subjective wellbeing (Diener et al. 2006; Dolan and Metcalfe 2012). These might include self-evaluations of what resilience is, what factors contribute to it, as well as whether or not people feel able to respond to current or future risks. A household's subjective resilience can be readily quantified if care is taken in designing suitable methodologies and survey questions (Maxwell et al. 2015; Béné et al. 2016a).

1.4. AN OBJECTIVITY-SUBJECTIVITY CONTINUUM FOR RESILIENCE MEASUREMENT

It is crucial to recognise that subjectivity and objectivity are neither binary nor mutually exclusive when it comes to resilience measurement. Objective measures will invariably have elements that are subjective in nature (and vice versa). At its simplest, subjectivity and objectivity can be thought of in relation to two core tenets:

i) How is resilience defined?

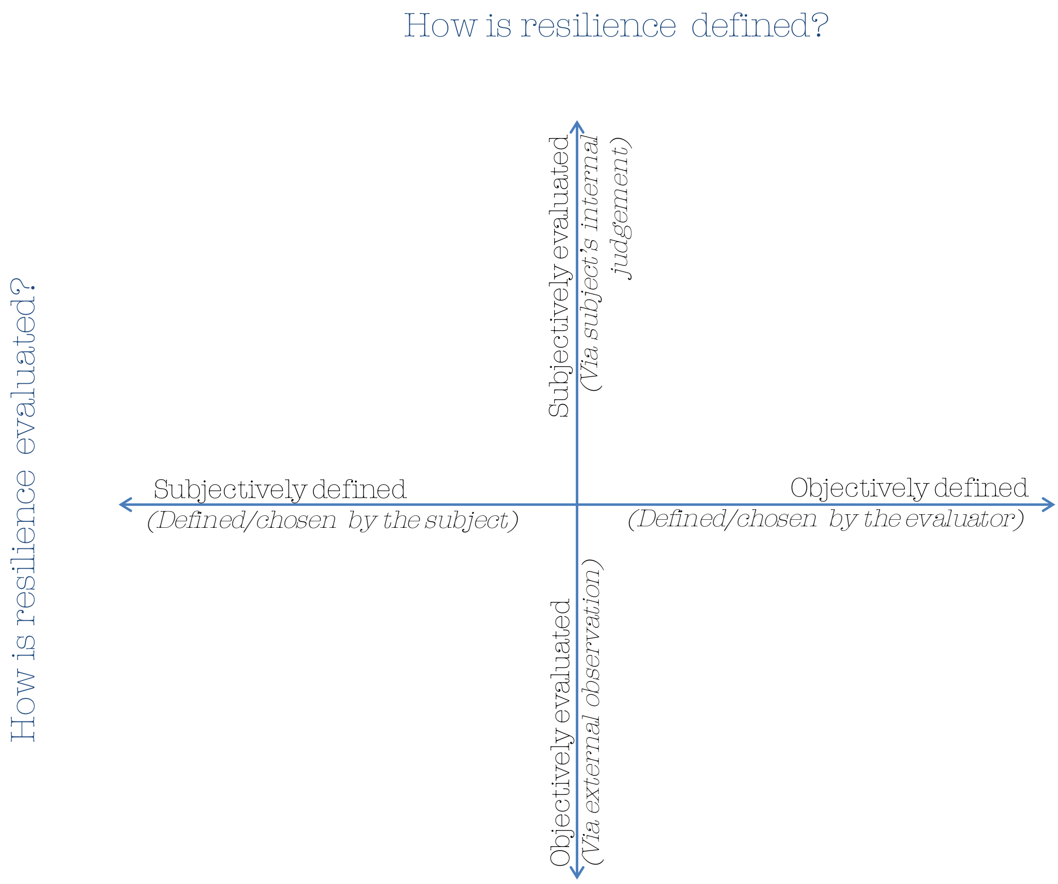
Objective approaches are externally defined (typically by the evaluator); subjective approaches are defined by the subject(s) in question.

ii) How is resilience evaluated?

Objective approaches are reliant on external observation; subjective approaches make use of a subject's own judgements and self-evaluations.

In thinking through the overlaps between the two tenets I propose that the relationship between subjectivity and objectivity is best thought of as a continuum. The objectivity-subjectivity continuum described in Figure 1 aims to aid researchers in identifying how resilience measures draw on aspects of objectivity and subjectivity. It helps to classify different types of resilience measurement tools, allowing the strengths and weaknesses of different subjective and objective elements to be readily identified.

Figure 1: The objectivity-subjectivity continuum of resilience measurement



1.4.1. Subjectivity and objectivity in how resilience is defined

As alluded to above, definitional ambiguities make the process of measuring resilience a considerable challenge. Researchers seeking to quantify resilience require clear specifications in how resilience is defined (i.e. what is resilience?). This also extends to how resilience is characterised – the various characteristics that make up a resilience person or community (i.e. what does resilience look like?). These can include a range of different capacities including absorptive capacity, adaptive capacity, transformational capacity and many others (Béné et al. 2012; Pelling 2010; Langston and Schipper 2015). As such I include characterisations within the concept of resilience definitions outlined below.

The choice of whether to subjectively or objectively define resilience is principally an issue of epistemology. One option is to have a standardised definition of resilience that is externally determined and fixed (i.e. the same framework of resilience is applied to everyone). This is typically guided by expert elicitation (whether by NGO staff or academics) or based on existing literature (Schipper and Langston 2015). Here resilience can be thought of as objectively defined and has little input from those being assessed, falling towards the right-hand side of the continuum.

Subjective definitions challenge this assumption. They operate on the basis that the respondent in question is better able to identify the factors that support their own resilience (as seen on the left-hand side of the continuum). The distinction is important given that stakeholders have different understandings of how a system's resilience is derived. Herrera (2017) demonstrates this poignantly using the case study of food systems in Guatemala. Here, different stakeholders are asked to elaborate on aspects they consider important in contributing to local resilience:

> "*While academics and delegates from the NGO participating in the study focused on enhancing virtuous cycles within the system, the central government delegates proposed solutions outside of the system's boundaries. All of these solutions, however, ignored the bounded rationality of the farmers and the premises of their decision-making process. Including only a few stakeholders in the process risks leaving many important aspects out of the scope of the analysis and therefore undermining its results.*" (Herrera 2017:14)

While there are approaches that sit at distant edges of the objectivity-subjectivity spectrum, in practice, most combine elements of both. For example, the approach adopted by the widely used Resilience Index Measurement and Analysis (RIMA) approach (D'Errico & Giuseppe 2014) sits firmly within the objective camp when it comes to its definition of household resilience. RIMA has a standardised definition comprised of five separate dimensions (called 'Pillars of resilience') and hundreds of individual indicators and proxies (FAO 2016). Statistical analysis of household survey data is then used to weight these dimensions and compute an overall scoring. While surveyed individuals are not asked to define what resilience means to them, nor what factors contribute to their own resilience, RIMA's approach can be seen to have some subjective elements. For example, the choice of each of the dimensions of resilience is based partly on extensive community-level engagements – people's perceptions and judgements of the factors that contribute to their own resilience – that then feeds up into the design of the overall framework (FAO 2016)[1].

At the other end of the continuum, subjectively-oriented approaches like the Community Vulnerability and Capacity Assessment (CVCA) and Tracking Adaptation and Measuring Development (TAMD) make a strong point of using communities to self-identify the characteristics of their own resilience (CARE 2009 and Brooks et al 2013). These are in turn used to formulate indicator-based scores and constitute the basis of their respective indexes. Yet, even these methods can be seen to have some degree of objectivity: community-defined fixed characteristics are inherently external to the individual or household being evaluated and require some degree of aggregation (what constitutes resilience for one household within a community may not be the same for all other households within it).

Things are further blurred when considering differences between the processes used to define resilience and the specific indicators used to measure them. To illustrate this, it is

[1] Note that this could only be considered as partly subjective in instances where households in the consulted communities are being assessed themselves

possible to conceive of an approach that has an externally determined characterisation of resilience, and then asks households within a community to identify their own local indicators matching the predefined capacities. This mix of objective and subjective elements would naturally sit towards the center of the continuum. It demonstrates not only the non-binary nature of clarification, but the complexities associated with classifying different types of approaches.

1.4.2. Subjectivity and objectivity in how resilience is measured

The second tenet of subjectivity and objectivity relates to the mode of evaluation (the y-axis in Figure 1). Once resilience has been defined, evaluators must decide how to quantify it. As there is no way of measuring resilience directly, objective evaluations often rely on proxy indicators of socio-economic data. For example, the Livelihood Change Over Time (LCOT) approach (Vaitla et al. 2012) uses 'household food insecurity and access' as one of its characteristics of resilience. This is measured through use of a separate index made up nine individual survey questions related to the household's food intake (Coates et al. 2007). Each of these can be largely thought of as objective: they are externally verified and require little in the way of subjective judgement – neither on the part of the respondent nor surveyor.

This contrasts markedly with subjective evaluations. Here, instead of using external observation, respondents are asked to self-evaluate levels of resilience using their own judgement. The properties of interest are typically people's perceptions, preferences and self-ratings of the status of their household or themselves (Maxwell et al. 2015). This is most commonly done using surveys that feature Likert scale response items (see Box 1 in the Strengths and Limitations section) and draw heavily on similar tools in the assessment of subjective wellbeing, psychological resilience and risk perception[2].

Again, it is difficult to conceive of approaches that fall strictly within objective or subjective categories. For example, many questions included in traditional household surveys can be thought of as objective in nature. For one, the LCOT assessment framework asks respondents the following question: 'In the past four weeks, did you worry that your household would not have enough food?' (Vaitla et al 2012). In practice, however, answers require the individual to internalise the question, interpret it based on their own understanding of the key concepts, and evaluate accordingly. For example, the notion of 'worrying' can be thought of as partly subjective, with the respondent prompted to define it as they see fit. Questions may also be affected by biases and heuristics that commonly affect survey responses such as priming, recall bias and social desirability (Dolan and Metcalfe 2012). Even relatively clear-cut objective indicators such as a household's distance to markets – an indicator used in the RIMA toolkit – rely on some degree of subjectivity (FAO 2016). For example, deciding what constitutes a 'market'

[2] Given limitations in the scope of this essay we only briefly delve into the advantages and drawbacks in these related fields. For more comprehensive summaries see Winkle et al. (2014), Weber (2010), OECD (2013) and Dolan and Metcalfe (2012).

requires internal judgement (either on the part of the evaluator or subject), and may not be understood uniformly.

1.5. CLASSIFYING RESILIENCE MEASUREMENT APPROACHES

In order to apply the continuum in practice, I compile a list of 17 prominent evaluation methods (see Table 2). The list details toolkits extracted from a range of recent reviews that include both objective and subjective measures, namely: Bours et al. (2014); Sturgess (2016); Constas et al (2016); Jones and Tanner (2016); Maxwell et al (2015); Claire et al (2017) and Schipper & Langston (2015). Here I am primarily interested in methods that examine resilience to climate variability and change at local levels, particularly those associated with individual and household level dynamics. Limiting the review to these scales allows for far greater comparability and nuance; community and national-level assessments often feature characteristics and indicators that differ markedly from those of localised evaluations (Adger et al. 2005; Vincent 2007) and reviews of their core features appear more prominently within the academic literature (Ostadtaghizadeh et al 2015; Shafiri 2016; Prior & Hagmann 2013). Accordingly, each listed framework is screened for suitability against the review's primarily criteria. Specifically: a main focus on disaster, climate or social resilience; an application at the individual or household level[3]; and the ability to generate a quantifiable metric of overall resilience.

It is important to note that this list is far from exhaustive. It aims simply to represent a body of widely applied methods, allowing for contrasting approaches to be identified and explored in detail. Using Table 2, I highlight the key differences in conceptual grounding and methods applied in the sections below (note that herein, references to the toolkits in Table 2 will relate to their abbreviated form, e.g. RIMA or MM07)

[3] Note that a number of toolkits have multiple scales of application, including some that are predominantly associated with community and national assessments. Toolkits were included in the list if they featured identifiable characteristics at local levels and where methods were readily applicable at the individual or household scales.

Table 2: Selected resilience measurement tools & respective modes of defining and evaluating resilience on the objectivity-subjectivity continuum

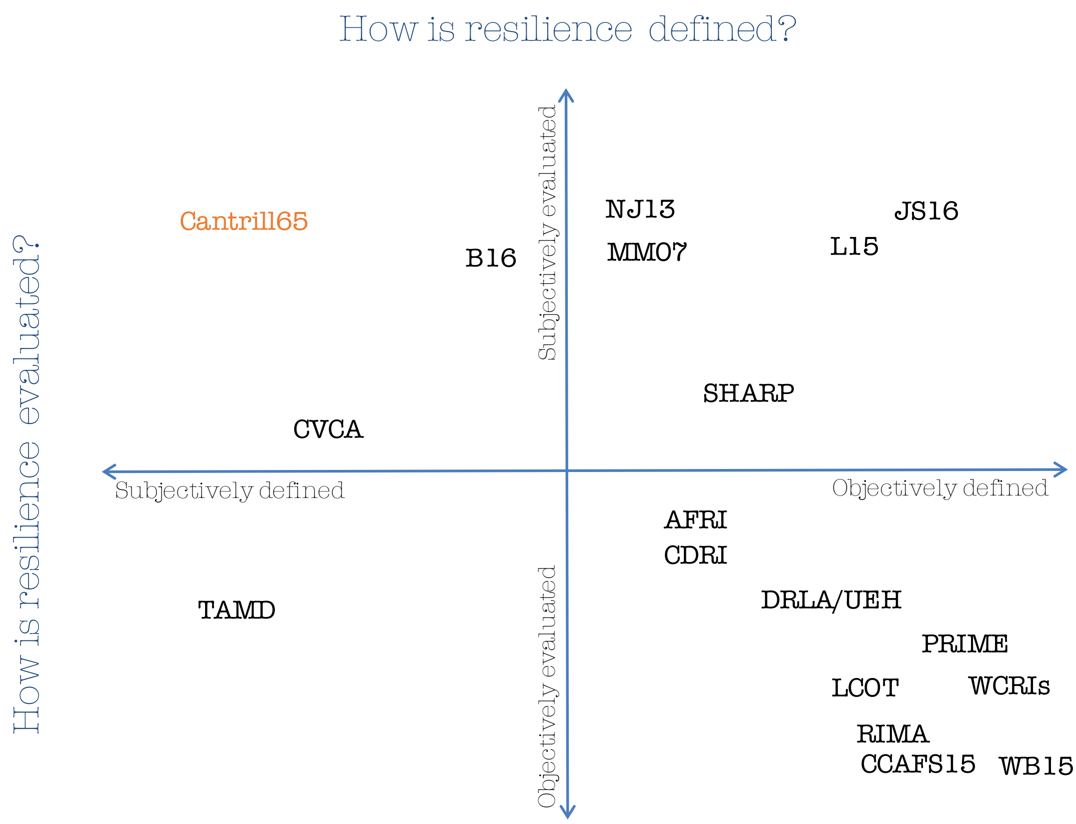
Framework	Primary Reference	Scale†	Intended purpose°	Who defines resilience? (*evaluator defined/chosen v subject defined/chosen*)	How is resilience measured? (*external observation v internal judgement*)
Alkire -Forster Resilience Index (AFRI)	Hughes & Bushell 2013	H	PE/SA	Resilience is comprised of 5 dimensions and 37 separate characteristics, based on conceptual frameworks taken from academic literature. The tool uses an adapted version of the Alkire-Foster method for measuring poverty. Cut off points for each indicator are reviewed by Oxfam field staff	Characteristics measured using external observation and household survey. A small number of perception-based questions
B16a	Béné et al 2016a	H	UR	A 'resilience index' is computed based on two subjectively defined characteristics: an individual's recovery from a past event and a community comparison. In addition, a measure of 'subjective resilience' is assessed as a household's ability to recover from a future hazard event. A household's resilience is then determined based on whether they are above or below a community-level average	Both the resilience index and subjective resilience levels are assessed using household surveys that employ psychometric self-evaluations with Likert scale response items. The former is a product of two self-evaluated questions (scores ranging from 1-30). The latter is a derived from a single ordinal question
CCAFS15	Hills et al. 2015	H/C	PE/SA	Resilience is characterised as having 3 core components and 9 indicator dimensions, based on available literature	Resilience is evaluated using a range of externally verified properties using household surveys
Climate Vulnerability and Capacity Assessment (CVCA)*	CARE 2009	H/C/N	SA	Resilience is not conceptually pre-defined. Rather its constituents are identified at the local level via community engagement exercises	Measurement is carried out through Participatory Rural Approach techniques with extensive use of perception-based queries
Community Disaster Resilience Index (CDRi)*	Mayunga 2007	H/C	PE/SA	Resilience defined using a 'capitals-based' approach, adapted from the DFID livelihoods framework. Each capital is weighted equally.	Index compiled using observations and household surveys
DRLA/UEH Evaluation Resilience Framework	Sylvestre et al 2012	I/H/C	UR/SA/PE	Resilience characterised as comprised of 7 dimensions. Dimensions and indicators are based on a combination of stakeholder consultation, review of academic literature and preliminary analysis of the household survey dataset	Assessment primarily through household surveys, with a small number of perception-based and subjective questions
JS16	Jones & Samman 2016	H	UR/SA	Resilience is predefined in relation to three core capacities: preparation; coping; and adaptation	Resilience is evaluated using a range of subjective questions involving self-evaluation
L15	Lowcock et al 2015	I	UR	Seven dimensions of resilience, and 85 individual indicators, identified through a literature review and tested with focus groups at the community level	Resilience is evaluated using a range of subjective questions involving self-evaluation
Livelihood Change Over Time (LCOT)	Vaitla et al 2012	I/H	PE/SA	Resilience characterised through a livelihoods approach and based on seven indicators of livelihood outcomes and household wellbeing (largely comprised of separate scales and indexes). Changes in resilience are measured over time	Assessments carried out through household surveys. Most feature observational quantities, with a small number of perception-based questions

MM07	Marshall & Marshall 2007	I	UR	Resilience is predefined as composed of 4 components (derived from 12 resilience-related statements) using Principal Component Analysis (PCA)	12 resilience-related subjective statements are used to assess resilience. Questions are delivered using surveys based on self-evaluations
NJ13	Nguyen & James 2013	H	UR	10 resilience-related questions designed through community focus groups, key informants and field observations	Resilience is evaluated using subjective questions involving self-evaluation
PRIME framework	Smith et al. 2015	H/C	PE	Resilience defined as 3 characteristics, each made up of a number of indicators and chosen on the basis of existing literature. An index is computed using PCA	Index is evaluated using household level surveys with a focus on objectively-verifiable quantities. Supplemented by qualitative focus groups and analysis
Resilience Index and Measurement and Analysis (RIMA)	FAO 2016	H	UR/PE/SA	Resilience is conceptualised based on available frameworks within the literature, particularly those used by the FSIN. Resilience is predefined as influenced by 4 core pillars, each with a number of individual indicators. Structure and weights for each are determined by statistical analysis	Assessment occurs via household surveys typically through external observation
Self-evaluation and holistic assessment of climate resilience of farmers and pastoralists (SHARP)	Choptiany et al 2016	I/H/C	UR/PE/SA	13 components of resilience based on Cabell and Oelofse (2012), further broken down into 54 indicators. A multi-criteria additive model is used to prioritise components of the resilience model	Assessment happens through questions administered through a household survey. This includes a mixture of observational questions as well as perception-based queries
Tracking Adaptation and Measuring Development (TAMD)*	Brooks et al 2013	H/C/R/N	UR/PE/SA	Adaptive capacity is not conceptually predefined but characterised based on context-specific features identified via community level consultations. Assessment framework combines aspects of adaptation with development indicators	Processes of evaluation are context specific though largely carried out on the basis of objectively verifiable indicators using household surveys. Some degree of perception-based indicators apparent
WB15	Alfani et al. 2015	H	UR	A household is considered resilient if there is very little difference between the pre- and post-shock welfare measured over time. Framework based on economic theory	Household survey data is used to evaluate resilience in relation to two qualities. Namely: household consumption and child nutritional deficiency. All quantities are externally verified
Weather and Climate-resilience Indexes (WCRIs)	Kimetrica 2015	H	PE/SA	'Weather-resilience' defined as an individual's average post-shock speed of recovery, or the average decrease in shock-induced poverty per period. 'Climate resilience' index defined as the average recovery time, given the expected distribution of weather shocks of different magnitudes	Resilience measured using traditional objective poverty measures administered through household surveys. Few perception-based questions

†*Scale codes: Individual (I); Household (H); Community (C); Regional (R); National (N)*. ° *Purpose codes: Understanding Resilience (UR); Project Evaluation (PE); Situational Analysis (SA).*
** CVCA, CDRI and TAMD are traditionally associated with qualitative assessments at the community-level, however each approach can be readily adopted in a quantitative manner and at household-level scales. While TAMD focused primarily on adaptation, it makes repeated reference to resilience capacities and is easily translatable to a resilience context.*

In gathering information on the 17 measurement toolkits it is also possible to group and place each directly onto the objectivity-subjectivity continuum. Doing so not only allows us to observe and compare different clusters, but points to gaps in current measurement approaches. Figure 2 reveals the outcome of this exercise. Assemblages of the various toolkits and the strengths and weakness of each quadrant are discussed below.

Figure 2: Common resilience measurement frameworks along the objectivity-subjectivity continuum



Notes: Cantril65 is a wellbeing framework used as a point of comparison discussed below. Placement of the frameworks is meant to allow differences to be readily compared and carried out entirely on the basis of the author's own judgement in assessing toolkit handbooks.

1.6. CLASSIFYING TOOLKITS AND MAPPING THEIR EVOLUTION

1.6.1. A brief history of objective methods of resilience measurement

While Table 2 and Figure 2 reveal a plurality of frameworks, several common features are evident. For a start, it is clear that almost all early measurement tools are objective in nature, particularly when it comes to defining resilience. Indeed, each framework shortlisted in Table 2 (with the exception perhaps of CVCA and TAMD) has some form of pre-defined characterisation of resilience used as a basis for evaluation. However, what this break-down looks like varies considerably. For example, several tools choose to adopt strict definitions of resilience guided predominantly by academic literature and theory. This is the case for World Bank's framework (WB15), which defines resilience as a household's change in welfare from pre- to post-shock states over time (Alfani et al.

2015). The Weather and Climate-resilience Indexes (WCRIs) have similarly strict definitions based largely on economic theory and the desire for a narrowly defined scope of assessment (Kimetrica 2015).

Others choose more iterative processes for characterising resilience. These may involve frameworks that are guided by the literature and technical experts, but also include some degree of input from communities of interest – often through the use of stakeholder consultations with local partners, focus group sessions and key informant interviews. For example, the DRLA/UEH Evaluation Resilience Framework and RIMA both adopt this strategy, choosing to combine external framings with some degree of localised input. Indeed, it is this latter category that is most prominent amongst the toolkits listed in Table 2.

Most objective tools opt to standardise: the same fixed framework is used for all households and individuals assessed. Once a characterisation of resilience has been set, indicators are then assigned to each component of resilience allowing an overall score to be produced. For household- and individual-level assessments these indicators will typically relate to key household assets or livelihood outcomes measured via a set list of externally verifiable questions and observations (MEL-CoP 2016).

1.6.2. The emergence of subjective methods of resilience measurement

Subjective tools have a much shorter history within the field of resilience measurement. While the early climate literature is replete with qualitative assessments that make use of subjective and perception-based methods (Twigg 2009, Miller et al. 2010, Gaillard 2010, Buikstra et al. 2010), few do so quantitatively. Perhaps the clearest initial example of a standardised quantitative subjective approach are the methods devised by Marshall and Marshall (2007; hereafter MM07) who assess 'social resilience' in commercial fisheries. Using MMO7's approach, individual perceptions are measured in accordance with pre-defined sentiments such as 'If there are any more changes I will not survive much longer', and measured using Likert scales.

Few subjective measures emerged immediately after MM07. However, recent years have seen a revival of perception-based tools within the resilience literature, with a suite of approaches developed in quick succession. Most notably, Nguyen and James (2013) devised a subjective model of household flood resilience that resolves around 10 attitude-based survey statements and the use of PCA. This was followed by a range of assessments by Lowcock et al (2015), Jones and Samman (2016), Seara et al. (2016) and Béné et al. (2016a). Much of this has been spurred on by the development of recent guidelines for the use of subjective methods in the context of resilience (Maxwell et al. 2015; Béné et al 2016; Jones and Tanner 2017; Claire et al. 2017).

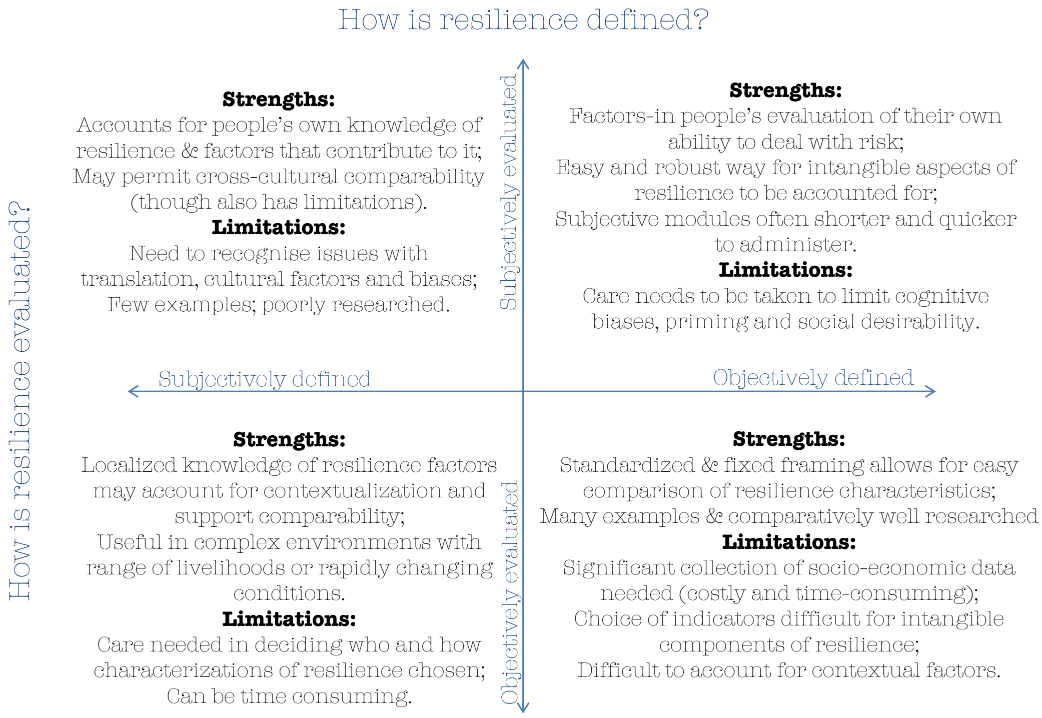
As evident from Box 1, many of the approaches listed in this review borrow heavily from related fields such as psychological resilience and risk perception. Indeed, in some cases it is difficult to make clear distinctions between the questions and methods of tools listed in Table 2 and Box 1 when compared with the common approaches in these neighbouring fields – such as the Connor Davidson Resilience Scale (Connor and Davidson 2003) or the Brief Resilience Scale (Smith et al 2008) used in the assessment of psychological resilience.

One main distinction is that the majority of tools used in the latter category place the individual psyche as the unit of assessment: how mentally-equipped is an individual to bounce back from trauma or devastation? Those applied in the context of resilience on the other hand are interested not just in the psychological components of resilience but the ability of individuals to draw on wider socio-environmental networks: does an individual or household believe that they have the capabilities and resources needed to deal with climate variability or change? Nevertheless, the differences are inherently subtle and mean that drawing distinctions is a particular challenge. Approaches such as those used by Jones (2018a) attempt to partially address this by focusing subjective-evaluations at the household level (see Box 1).

1.7. STRENGTHS AND LIMITATIONS OF COMMON MEASUREMENT APPROACHES

Deciding on whether to use subjective or objective methods is a process of neither right nor wrong. Each approach will offer evaluators certain benefits and drawbacks that need to be weighed up. Indeed, elements of both are likely to feature in any assessment of resilience, as underscored by the continuum. In attempting to guide evaluators in the choice of relevant toolkits I group key advantages and limitations into the four quadrants along the objectivity-subjectivity continuum. Figure 3 summaries these main attributes graphically and elaborated upon in the sections that follow.

Figure 3: Summary of key strengths and limitations of measurement approaches along the objectivity-subjectivity spectrum



1.7.1. Objective characterisation, objective evaluation

Approaches that fall into the lower right-hand quadrant of the continuum (i.e. objective definition and objective evaluation) constitute the majority of existing frameworks. Reasons for this are numerous. For a start, objective definitions allow for the same properties of resilience to be evaluated across households. When coupled with large sample sizes, evaluators can be relatively confident that similar capacities are being measured: the same fixed definition and characterisation of resilience will be measured in household A as for household B (I return to ask whether they are capturing the same underlying properties in the sections that follow). Standardisation of this sort also permits easy comparison across households and social groups. Moreover, it allows evaluators to hone in on specific capacities or indicators of interest. This is particularly relevant in cases where development actors may be concerned with the provision of targeted services, such as early warning systems focused on anticipatory capacity or social safety nets focused on absorptive capacity. Fixed framings of resilience of this sort enable evaluators to determine whether their interventions have an impact.

Toolkits in this quadrant are not without their weaknesses. For example, approaches that rely on objective evaluations require considerable amounts of socio-economic data to be collected. Indeed, most frameworks in this category focus on the measurement of resilience-related capacities (Béné et al. 2012). These are inherently intangible, with no one indicator able to adequately capture the processes that make up any given capacity (Jones et al. 2010). As such, distilling a household's capacity to cope in the face of climate extremes down to a single indicator is not only challenging but in most cases misleading.

Most objective approaches to evaluation therefore assign a large number of proxy indicators to each capacity, hoping to capture a range of different elements that relate to parts of the overall capacity (Constas et al. 2016). For example, the CCAFS15 framework measures adaptive capacity by identifying four 'indicator dimensions', each evaluated using multiple individual indicators assigned to them. Inevitably, this not only requires judgement calls as to which mix of indicators is appropriate (both in terms of theoretical relevance and availability of data) but makes the processes of data collection lengthy and cumbersome (MEL-CoP 2016). Resilience measurement questionnaires of this sort, such as RIMA, can therefore take multiple hours to carry out for each household interviewed given the number of questions and proxy indicators included within (FAO 2016).

More importantly, by fixing the definition and indicators of resilience, evaluators risk undermining the validity of one of their principle aims: across-household comparability. It is well known that the resilience of individuals and households is context specific (Adger et al. 2005). With that in mind, the factors that contribute to the resilience of a local trader in Nairobi, Kenya may differ considerably from those of a fisher in coastal Mombasa. While the former may be heavily dependent on local market price volatility and the security of their available stock, the latter may rely more on the health of adjacent fisheries and the ability of their boat to withstand turbulent seas during extreme weather events. Clearly, using the same set of indicators to measure the resilience of both individuals would be problematic. Thus, a key question for toolkits with objective characterisations of resilience is: do the chosen characteristics and indicators of resilience truly reflect the resilience of each individual in question? Care must be taken with any cross-cultural comparison as the answer is rarely yes. However, these types of approaches may be best suited to evaluating individuals and households that share similar contexts – whether in relation to livelihoods, climate or geography.

1.7.2. Objective characteristisation, subjective evaluation

Approaches in the upper right-hand quadrant of the continuum constitute the majority of existing toolkits associated with subjective resilience. They often involve fixed evaluator-defined definitions of resilience, and allow respondents to self-evaluate their resilience capabilities accordingly. Box 1 provides examples of self-evaluated response options from a range of different toolkits that fall under this category of assessment.

Box 1: Examples of perception-based statements used in a number of subjective toolkits

MM07 (subset of 3 from 10 statement)

i. I can cope with small changes in industry.
ii. I am more likely to adapt to change compared to other fishers.
iii. If there are any more changes I will not survive much longer.

Statements rated on a 4-point scale: 1 = strongly disagree, 2 = disagree, 3 = agree, 4 = strongly agree.

L15 (subset of 3 from 85 statements)

i. I am willing to try new things
ii. In times of change I am good at adapting and facing up to challenges
iii. I am still able to manage my property well during the tough times

All statements employ a 1-5 scale, where 1 = strongly disagree and 5 = strongly agree

JS16 (subset of 2 from 3 statements)

i. If an extreme flood occurred in the near future, how likely is it that your household could recover fully within six months?
ii. If extreme flooding were to become more frequent in the future, how likely is it that your household could change its source of income and/or livelihood, if needed?

All statements employ a 4-point scale: (1) Extremely likely; (2) Very likely; (3) Not very likely; (4) Not at all likely

Jones 2018 (subset of 2 from 9 questions)

i. My household can bounce back from any challenge that life throws at it
ii. If threats to my household became more frequent and intense, we would still find a way to get by

All statements employ a 1-5 scale, where 1 = strongly disagree and 5 = strongly agree

B16

i. With respect to [EVENT], how well do you consider you managed to recover?
ii. With respect to [EVENT], how well do you consider you did, compared to the rest of the community?

Response items for i) are as follows: Not at all and I don't think I will be able to recover; Not yet fully recovered and it will be difficult/long; Not yet but hope very soon; Have fully recovered but it was long and painful; Have fully recovered and it was not too difficult; Have fully recovered and I am better off now. Response items for ii) are as follows: Did worse than most of the others; As bad as some people but better than others; Like most of the others; Did better than most of the others; Did better than anyone else.

For full details of the methods and questions used see original citations: Marshall and Marshall (2007); Lowcock et al. (2015); Jones and Samman (2016); Jones (2018a); Béné et al. (2016).

Though approaches such as JS16 and B16 have predefined characterisations of resilience (and can therefore be considered somewhat objective) they offer one way of addressing the issue of cross-cultural comparability. Instead of assigning fixed indicators to each characteristic of resilience, these toolkits allow the individual in question to self-evaluate themselves accordingly. In theory, given that the local trader and fisher are far more familiar with their individual circumstances and capabilities, and are being asked to weigh up the factors that support their own resilience, this method should generate scores that can be compared. Much of this relies on the assumptions that people have broadly similar understandings of what resilience constitutes and are in a good position to self-evaluate their own risk-profiles (Jones and Tanner et al 2017). More importantly, the fact that the individual is factoring in their own knowledge of what makes them resilient and the risks that they face around them may imply that subjective methods are a more holistic and accurate reflection of the respondent's 'true' resilience. This is particularly the case when compared to standardised indicators-based approaches that cannot take localised factors into account.

If the above assumptions hold true, then subjective evaluations may be of considerable relevance to project evaluators seeking to measure the impact of resilience-related interventions over time. They offer a more bottom-up and participatory way of assessing resilience that places greater value on people's own understanding and judgement. Another key advantage relates to survey length and duration. Many objectively-oriented measures of resilience require several hours of household surveying, owing to their dependence on large lists of proxy indicators. Contrastingly, a subjective evaluation can be carried out with just a handful of questions – through admittedly with less detail and complexity (Jones and Tanner 2017). This flexibility can not only help to reduce the burden of 'survey fatigue', but opens possibilities for greater innovation in survey delivery. More importantly, subjective evaluations can play an important role in holding NGOs and governments to account in relation to commitments and interventions; in theory, effective investment into resilience-building activities should be felt by those that are receiving support and having to deal with climate risk[4].

In practice, these assumptions should be considered carefully when interpreting the results of any subjective evaluation. For one, they depend heavily on people's interpretation of key definitions. 'Resilience' is used in everyday language and means different things to different people. It also has varied meanings across languages and cultures (Crane 2010). For these reasons, Jones and Tanner (2017) suggest that subjective measurements of this sort may not be suited to single-item questions, as is commonly found in measures of subjective wellbeing (OECD 2013). Rather, subjective evaluations may benefit from breaking resilience down into questions that relate to easily communicable and translatable processes, such as: the ability to prepare for an upcoming extreme event; the ability to rebound quickly; and the ability to adapt to emerging future threats. This also avoids the need to use the word 'resilience' in survey questions.

A further issue that needs to be considered is inter-personal and cross-cultural differences in responding to standardised questions. For example, two people might consider the circumstances of the same household and rate them very differently based on what they consider to be a 'normal'. One way of addressing this challenge may be through the use of anchoring vignettes (Hopkins and King 2010). These are hypothetical narratives provided to people at the start of a survey. For example, an anchor might describe a household that has recently been affected by a drought and has had to sell off a number of livelihood assets as a result. People are then asked to rate the circumstances of the

[4] This assumption may apply more to investments in tackling current risk profiles (particularly covariate risk) as the impact of those addressing longer-term or idiosyncratic shocks may not be felt by recipients for a long time.

hypothetical household before rating themselves according to the same response scale. This allows for benchmarking of responses and is a way of explaining theoretical definitions of complicated concepts (King and Wand 2006). It is worth noting that these methods have yet to be applied in the context of resilience measurement but offer promise in addressing some of its limitations.

1.7.3. Subjective characterisation, objective evaluation

Approaches that occupy the lower left quadrant of the continuum are those that first seek respondents to define or characterise resilience themselves, before evaluating them objectively. Here individuals (or members of a community) are asked to identify what makes them resilient. Objective indicators are then agreed upon to track levels of resilience using a similar consultative exercise. For example, a community might decide that the factors that contribute most strongly towards a household's resilience are levels of education and proximity to health care facilities. In this case, while the indicators are subjectively chosen, the process of evaluating them is inherently objective: they involve external verification, and little if any subjective judgement on the part the respondent. Note that it would certainly be possible for a measurement tool to allow individual households (or people) themselves to define resilience and objectively evaluate them accordingly. This would place the toolkit further towards the left-hand side of the continuum. In practice, few measurement toolkits have adopted this approach to date. Indeed, the TAMD approach is the sole example from amongst the shortlisted toolkits in Table 2.

Toolkits in the lower-left quadrant of the continuum are particularly useful in trying to assess households in contexts where factors supporting resilience might be unknown or difficult to identify externally. They may even be applied in situations where characteristics of resilience change over time - a household could be asked to re-identify suitable indicators at each round of a panel survey for example. The advantage of these techniques is similar to those of all other subjective approaches: they provide a way of contextualising resilience measurement and offer a more holistic conceptualisation of resilience that factors in people's own knowledge of their capabilities and capacities.

Furthermore, objective evaluation helps to ensure that cognitive biases in self-reporting are largely (though not wholly) accounted for. The drawback is that the set of indicators chosen by one household (or community) may be wildly different from those of another. Evaluators that favour standardised approaches may therefore be reluctant to use these methods for cross-cultural comparison – though an argument could easily be made that self-selection of indicators means that comparison is in fact more robust. Getting households and communities to define resilience can also be very time consuming and requires excellent facilitation as the exercise is repeated constantly. This is perhaps the principal reason why so few examples of this type of approach exist – especially when applied at the household or individual level.

1.7.4. Subjective characterisation, subjective evaluation

The last group of toolkits relates to those in the upper-left quadrant. Just like the processes listed above, households or communities are asked to identify factors that constitute resilience from their own perspective. Households are then tasked with self-evaluating themselves according to their own definitions. This could apply to one of two models depending on whether resilience is further broken down into individual factors. A household could, for example, identify that their capacity to adapt to climate change is largely dependent on two qualities: their ability to make arrangements for their own financial security; and their ability to learn new skills in the labour market. A questionnaire could then be devised asking the respondent to answer the extent to which they agree or disagree with the following: 'I believe that my household has made adequate plans for its financial security', or 'Members of my household are able to learn new skills outside of the industry' (Marshall and Marshall 2007). In some ways, this approach is similar to the methods used by the CVCA toolkit. CVCA relies heavily on community consultations to define resilience before applying mixed methods approaches for its evaluation[5].

A much simpler method would be to pose a single question asking people to measure their own resilience, such as 'to what extent is your household resilient to the impacts of climate change'. Here the respondent not only has to internally define what resilience means to them, but consider the factors that contribute to it before self-evaluating accordingly (Claire et al 2017). There are few existing measures that adopt this single-item approach. Perhaps the closest is that used by Béné et al. (2016a) that ask 'With respect to [a specified prior event], if it was to happen again in the near future how do you consider you would be able to recover?'.

The overall approach is very similar to measures of subjective wellbeing such as the Cantril ladder - inserted into Figure 2 for illustrative purposes (Diener 2000; Kahneman and Krueger 2006). It asks people to imagine a ladder with steps numbered from zero at the bottom (representing the worst possible life) to 10 at the top (best possible life), before asking: 'which step of the ladder would you say you personally feel you stand at this time?' (Cantril 1965). The ladder and other related methods have been used in a wide variety of contexts and have been shown to have validly in reflecting core components of an individual's quality of life (Diener 2012; Helliwell and Barrington-Leigh 2010). Indeed, measures of subjective wellbeing are beginning to have strong influence in guiding policy at national and international levels (Layard 2005; Dolan et al. 2011).

There are certainly grounds to argue that a similar single-item approach to resilience measurement could be robust. After all, 'happiness' or 'life satisfaction' are as nebulous and diverse as the concept of 'resilience'. Clare et al. (2018) offer another such option that may hold promise. They ask respondents to assess how they expect to fare if they were to experience a range of self-selected shock events using a single-item question. However, many of the same limitations apply to single-item approaches as for

[5] Strictly speaking, CVCA is typically used in the context of qualitative analysis. However, it's methods can be readily applied to quantification and is largely used for illustrative purposes in this example.

measurements of wellbeing (OECD 2013). For one, a single-item question would not allow an evaluator to isolate specific characteristics of interest – resilience is multi-dimensional after all (Nagoda 2015). It would also be difficult to disentangle resilience to particular hazards unless explicitly stated in the question (as Claire et al. 2018 do with follow-up questions).

Above all, subjective approaches (of any sort) face the challenge of preventing survey responses from being affected by cognitive biases and heuristics. Insights from psychology and behavioural economics show that effects such as the Peak-End rule (Tiberius 2006), impact and retrospective bias (Durayappah 2011) as well as hedonic adaptation (OECD 2013) can each have a strong influence on how people assess themselves. Priming, a psychological process in which exposure to a stimulus can trigger a concept in memory that is then given increased weight in subsequent judgment tasks, is another key factor to consider (Lavrakas 2008). While these issues are common to all social science surveys, evaluators should take great care in deciding: how questions on subjective resilience are framed; the placement and order of questions on a survey; and the contextual environment within which respondents are being asked to answer questions.

1.8. KNOWLEDGE GAPS AND AVENUES FOR FUTURE RESEARCH

Given the relative infancy of scholarly research on resilience measurement several key knowledge gaps remain.

Firstly, little is known about how different toolkits measure the same respondent: few like-for-like comparisons have assessed whether one approach generates results that are comparable to others. This not only applies to comparisons of subjective and objective measures, but also measures that adopt the same general approach. Understanding the implications of using different characterisations of resilience and sets of indicators lists is important when considering the wide range of methods applied across available toolkits. Indeed, the diversity of definitions of resilience within the academic literature allows evaluators to justify almost any combination in designing measurements tools (Olsson et al. 2015).

It is also important to recognise that different measurement choices will lead to differences in measured outcomes. For example, a framework that includes transformation in its characterisation of resilience may deliver different results from one that does not. The situation is even more apparent with measurement approaches that employ subjective characterisations of resilience (as each person may have their own interpretation of the characteristics). This has considerable implications for programme M&E, and requires evaluators to be more transparent in the choices and assumptions made in choosing measurement tools – whether subjective, objective or a blend of the two.

Secondly, establishing whether factors correlated with objectively-evaluated resilience match subjective evaluations is of keen interest. Early insights from studies by Jones and Samman (2016) and Béné et al. (2016a; 2016b) show that many socio-economic indicators are poor predictors of subjectively-evaluated resilience – posing a potential challenge to traditional objective assumptions. Insights from the wellbeing literature reveal that in many cases subjective and objective measures display weak relationships and can correlate with different socio-economic factors (Cummins et al. 2003). Clarifying the relationship between the two approaches will therefore be key to improving our understanding of factors that support resilience. It may also serve to produce more holistic and robust methods of evaluating development and humanitarian interventions.

Thirdly, given the recent emergence of subjectively-oriented measures of resilience, several avenues for future research exist. Understanding how cognitive biases and priming affect self-assessments of resilience is a useful first start – drawing on existing literature of survey methods and applications (Tiberius 2006; Durayappah 2011; Lavrakas 2008). Doing so will allow evaluators to design more effective surveys and test the validity of scores related to objective measures. A further area of development relates to how subjective questions are structured. While some subjective measures ask respondents to reflect on past climatic events (as per the 'resilience index' in B16), others focus on hypothetical future events (NJ13 and JS16). Toolkits also differ in the extent to which they measure resilience to specific hazards, or a range of unspecified risks (as adopted by MM07 and Jones 2018a). Establishing the implications of these choices, and appropriate occasions for their use, is imperative given the that results are likely to differ considerably (Jones 2018b). Here again, much can be drawn from related literatures on subjective wellbeing and risk perception (Dolan et al. 2011; OECD 2013)

Finally, our understanding of whether subjectively-oriented measures of resilience differ across contexts has a number of clear gaps. For example, though subjective tools have been applied in both developing (Waters and Adger 2017; Nguyen and James 2013; Béné et al. 2016b; Jones and Samman 2016) and developed country contexts (Seara 2017; Marshall 2010; Lockwood et al 2015), more can be done to understand how differences in environmental, socio-cultural and cognitive factors shape people's responses. More importantly, a wide body of literature explores normative and societal influences on people's response to risk (Rutter 1987; Paton 2003), as well as the importance of heuristics in decision making and human behaviours (Kahneman and Tversky 1979). Yet, few resilience measurement toolkits have accounted for these in their approaches warranting further exploration.

1.9. CONCLUSION

Interest in resilience measurement continues to grow, thanks in large part to a growing community of measurement practitioners such as the FSIN network and the Rockefeller Foundation's Resilience Measurement Community of Practice (MEL-CoP). The subject is also receiving increasing amounts of financial and technical support from traditional development funders eager to track the effectiveness of their resilience-building investments. While these advancements are inherently positive, ambiguity and confusion persist regarding the merits and limitations of different measurement approaches. More recently, the advantages of subjective approaches have been trumpeted with a growing number of studies making us of them (Clare et al. 2017).

In this paper, I provide greater clarity in understanding the distinctions between objective and subjective ways of assessing resilience through use a novel continuum. The objectivity-subjectivity continuum highlights two core tenets, i) how resilience is defined (whether by the evaluator or the subject being observed), and ii) how resilience is measured (whether by external observation or internal judgement). I also showcase the assumptions and weaknesses of toolkits associated with the four quadrants of the subjectivity-objectivity continuum.

In highlighting the use of different approaches, it is important to emphasise that there is no one-size fits all approach to resilience measurement. Evaluators should ultimately consider a number of factors before choosing which toolkit to adopt, including: their epistemology of knowledge creation; core objective of the measurement exercise; and resource and data constraints. Most importantly, clearer insights into the relationship between subjectivity and objectivity can improve our understanding of resilience. Guiding the design and development of interventions aimed at supporting it.

Chapter 2

Resilient, but from whose perspective?

Like-for-like comparisons of objective and subjective measures of resilience

Lindsey Jones and Marco D'Errico

As resilience continues its rise to top of the international policy agenda, development practitioners are under mounting pressure to ensure that investments in resilience-building are effective and targeted at those most in need. It is here that robust resilience measurement can make valuable contributions: identifying hotspots; understanding drivers; and inferring impact. To date, resilience measurement has been dominated by objectively-oriented approaches. These typically rely on external definitions of resilience, and are measured through observation or external verification. More recently, the potential for subjective approaches has been proposed. These take a contrasting approach, soliciting people's judgements of what resilience means to them and asking them to self-evaluate accordingly.

While both approaches have their strength and weaknesses, little is known about how objective and subjective modes of resilience measurement compare. To shed light on this relationship, we carry out a like-for-like comparison of the two approaches using a regionally representative household survey of 2,308 households in Northern Uganda. In so doing, we introduce a new measurement approach named the Subjective self-Evaluated Resilience Score (SERS). Outcomes from SERS are directly compared with an objectively-evaluated approach, the Resilience Index Measurement Analysis (RIMA) – widely used by resilience practitioners.

Findings from the survey suggest a moderate correlation between objectively- and subjectively-evaluated modules. More importantly, both approaches share similar associations with many key socio-economic drivers of resilience. However, there are notable differences between the two. In some case, the approaches diverge entirely with regards to contributions of important traits. This includes associations with coping strategies, levels of education and exposure to prior shocks. Our results highlight the need for resilience evaluators to consider a diversity of knowledge sources and seek greater use of evidence in indicator selection. We also investigate the properties of the SERS module itself. We find that characterisations of resilience designed to mimic various commonly-used resilience frameworks produce similar outcomes. In addition, shorter SERS modules match the performance of the full set of SERS questions, allowing for quicker administration and reduced survey burden. Lastly, we call for evaluators to consider the strengths and weaknesses of subjective and objective measurement approaches, including options for combining both formats.

2.1. INTRODUCTION

As political support for resilience intensifies, development and humanitarian actors are under mounting pressure to find robust ways of evaluating the effectiveness of resilience-building interventions (Roberts et al. 2015; COSA 2017). A wide range of measurement approaches have recently sprouted in seeking to address this need (Schipper and Langston 2015; Brooks et al. 2019). To date, the vast majority of these rely on objective forms of measurement (Bahadur and Pichon 2017). Broadly speaking, objective approaches can be described as those reliant on judgements or observations that are external to those being measured. Here objectivity can relate to two aspects: how resilience is defined, i.e. who decides what resilience is and the characteristics that make a household resilient?; and how it is measured, i.e. is resilience measured by means of external observation or self-evaluated judgements? (Jones, 2019).

Objective measures of resilience have many advantages. For example, most: use fixed and transparent definitions of resilience (Clare et al. 2018; Beauchamp 2019); allow for different groups of people to be compared through standardised metrics (COSA 2017); and rely on proxy indicators gathered through large household surveys – many of which are routinely collected by governments and development agencies (Schipper and Langston 2015). Yet they also face considerable draw-backs (Levine 2014). For one, agreeing on a common set of resilience indicators has so far proven a considerable challenge – despite numerous syntheses and technical reviews (Schipper and Langston 2015; Bahadur and Pichon 2017; FSIN 2014a).

In addition, while household resilience is partly driven by the availability of physical assets and infrastructure, much of it also relates to 'softer' elements. These are often made up of intangible processes – such as community cohesion or social capital – and are difficult to see or measure (Adger 1999). Objectively-evaluated tools often use large lists of proxy indicators to account for an inability to directly observe them (Bahadur and Pichon 2017). Yet, doing so requires significant amounts of socioeconomic data– much of which is difficult to collect in post-disaster contexts and poorly available across the Global South (COSA 2017). More worryingly, a preference to opt for easily quantifiable capacities not only risks skewing measurement outcomes but shifts consensus narratives on the determinants of resilience (Clare et al 2018).

Most importantly, objective approaches do not currently take into account the wealth of knowledge that people have of their own resilience and contextual information that can help to inform it (Marshall and Marshall 2010). This includes important internal factors such as mental states, aspirations and psychological resilience. Each of which is fundamental in shaping how households react in the face of external threats (Cox and Perry 2011). With these factors in mind, alternative methods of resilience measurement have recently been sought (Maxwell et al. 2015).

One promising approach comes in the form of subjective tools of assessment (Marshall 2010; Jones and Tanner 2017; Jones and Samman 2016; Claire et al 2017; 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 valid understanding of the risks they face (Jones 2019). As with objective measures, subjective approaches can relate either to how resilience is defined or how it's evaluated. They use people's own judgement of what constitutes resilience and self-evaluations of their ability to deal with risk. Crucially they place few, if any, constrains on what a respondent should consider in assessing their own resilience: measurement is largely done by the respondent themselves[6].

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 traditional objective approaches (Maxwell et al. 2015; Clare et al. 2017). Yet, in practice, we know very little about the relationship between objective and subjective forms of resilience measurement. In this paper, we address this gap in knowledge by comparing objective and subjective measures of resilience using a regionally-representative survey in Northern Uganda. To do so, we introduce a new subjective approach, termed the Subjective self-Evaluated Resilience Score (SERS). SERS asks respondents to self-evaluate their own household via a series of nine capacity-related questions. We use this module to make like-for-like comparisons between SERS and an objective measure, the Resilience Index Measurement Analysis (RIMA).

Data from the survey are used to examine three research questions. Firstly, given that each household in the survey is assigned both SERS and RIMA modules, we look at how subjective and objective-measures of resilience compare. Secondly, we take advantage of the wide range of livelihood information collected during the survey to examine whether SERS is associated with the same socio-economic drivers and indicators as RIMA. Our last research question looks at the properties of our subjective module in more detail. Specifically, we are interested in knowing whether different variants of SERS produce similar resilience outcomes.

In answering these three queries we stress that neither SERS nor RIMA are 'true' measures a household's resilience. Given that resilience is not directly observable (DFID 2015), they offer two different ways of inferring resilience outcomes. Yet, considerable value can still be taken in examining how the properties of the two compare. This is especially relevant in testing assumptions that underlie selection of characteristics and indicators for resilience measurement.

We structure our paper as follows. We start by providing background information on resilience and ways of measuring it. We also clarity distinctions between subjective and objective forms of measurement. Next we detail our methods, including the properties of the survey as well as the SERS and RIMA modules used within it. We then present results, followed by a discussion structured around the paper's three primary research

[6] Subjectively-oriented questions should allow for respondents to internally consider and validate their own understanding of resilience, with outcomes feeding into a quantitative measure.

areas. Lastly, we finish with a brief description of limitations and ways forward for the resilience measurement community of practice.

2.2. BACKGROUND AND CONTEXT

The notion of resilience has a long history spanning multiple academic disciplines (Alexander 2013). In recent decades, the term has gained prominence across the sustainability sciences in describing how socio-ecological systems respond to shocks and stresses. The rise in popularity has coincided with the adoption of resilience as a unifying framework in bridging humanitarian and development practices. Indeed, resilience is now central to a number of international policy commitments, including the UN's Agenda 2030 and Paris Agreement on climate change (United Nations 2015a,b). While its prevalence has helped to raise awareness for risk reduction, it has also contributed to considerable debate and confusion around the term's actual meaning.

Historical applications of resilience (mainly those stemming from engineering and ecology) have long been associated with the ability of a system to return to a normalised state after disturbance or change (Holling 1973; Walker et al. 1981). This clearly has many parallels for social systems. However, social scientists were quick to highlight the importance of unique social processes such as adaptation and transformation. These preemptively allow societies to respond to threats like climate change or environmental degradation (Pelling 2010; Miller 2010). In some ways, these can be seen as at odds with notions of resilience as bouncing-back, further contributing to conceptual ambiguity (Olsson et al 2015).

Discrepancies like these have considerable implications for measurement efforts. Given that resilience cannot be directly observed, most measurement approaches choose to break resilience down in its constituent characteristics (DFID 2016, Bahadur & Pichon 2017). Whichever mix of characteristics is chosen by the evaluator will inevitably play a large role in dictating measurement outcomes: and is partly responsible for the vast number of different resilience tools that have emerged in recent years (Schipper & Langston 2015). To complicate matters, resilience-related characteristics are seldom observable in themselves (Brooks et al. 2019). In the case of objectively-evaluated frameworks, tools often address this challenge by resorting to large lists of proxy-indicators tied to socio-economic traits or other development outcomes (see HSSAI 2015 and Bahadur & Pichon 2017 for a review of different approaches).

With the above in mind, we focus our analysis on a narrow definition and application of resilience. Specifically, we hone in on a particular unit of analysis: the household. This is due to the centrality of the household unit in dictating responses to external stimuli whether at the individual, family or 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). A focus on households also allows for distinctions to be drawn between psychological resilience – associated with the ability of an individual's psyche to deal with shock or trauma – and the resilience of the individual or household overall. This point is particularly relevant when assigning modules on subjectively-measured resilience (Windle et al. 2011). However, we recognise that our focus on households limits our ability to examine the relationships important cross-scalar issues. It also tells us little about the contribution of intra-household dynamics to resilience – particularly in relation to power dynamics and social ties that exist between household members (Carr 2005).

Before any effort at measuring resilience can start, one question has to be clarified: what are households resilience to? Resilience can be defined in relation to a specific hazard (or related set of hazards) (Brooks et al. 2019). The literature is replete with examples, including flood resilience (O'Sullivan et al. 2012); drought resilience (Keil et al. 2008); or climate resilience more broadly (Tyler & Moench 2012). Conceptually, the idea is to examine the ability of a given system (in our case a household) to cope with and respond to a particular hazard. However, hazards rarely occur in isolation. Households often have to contend with exposure to multiple overlapping risks (O'Brien & Leichenko 2000; Kelman 2010; Zobel & Khansa 2011). As such, resilience is increasingly referred to in relation to broader systemic risk or outcome-related traits - such as disaster resilience (Cutter et al. 2010), food systems resilience (Pingali et al. 2005) or economic resilience (Rose 2004). Here, resilience is thought of as the ability of a system to maintain wellbeing outcomes in the face of diverse multi-hazard environments. Many of which may interact in threatening a household's basic functions:

> '*Climate change, globalization, poverty, earthquakes, injustice, tropical cyclones, lack of livelihood opportunities, inequity, landslides, overexploitation of natural resources, epidemics, and lack of water supply—amongst many other ongoing challenges—often converge to most affect those who have the fewest options and resources for dealing with those challenges. Consequently, those with the fewest options and resources tend to be most vulnerable across all forms of threats, demonstrating multiple exposure to multiple threats simultaneously'* Kelman et al. (2010:23)

In the context of this study our focus is on Karamoja, Northern Uganda. More so than any environment, Karamoja is one facing a wide range of overlapping threats: a confluence of colonial subjugation, regional and tribal isolation, and a harsh natural environment (Levine 2010). Accordingly, we concentrate our analysis on a broad multi-risk conceptualisation of resilience. However, we recognise the importance of single-hazard approaches, and seek to compare our main results with these where-ever relevant (see Robustness checks below).

Another important point of clarity relates to the distinction between objectivity and subjectivity. For the purposes of this paper we make use of the objectivity-subjectivity continuum proposed by Jones (2018b). The continuum refers to objectivity and subjectivity in resilience measurement by isolating two core tenants. The first is how resilience is defined. Objective definitions of resilience can be classed as those 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 (Schipper and Langston 2015). Objective characterisations also tend to be standardised and fixed in their depiction of resilience and its properties (Jones 2019). On the other side of the continuum, subjective measurement tools draw primarily on the judgement of those being measured themselves. This means that individuals (or a collection 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 measurement. Objective approaches to resilience rely on external observations and verification, i.e. little to no room for the judgement and perspectives of those being measured. For example, use of satellite imagery to evaluate the extent of damage to a property, or an assessment of household assets through a household survey can both be seen as objective measures. They involve little, if any, subjective judgement on the part the respondent. On the other hand, subjective assessments make use of people's perceptions in the measurement process itself. They typically involve asking respondents to self-evaluate themselves, drawing on their own internal judgement of their household's ability to deal with risk. The same approach is often used in evaluating subjective wellbeing, where people are asked to self-assess levels of life satisfaction or happiness (OECD 2013; Dolan and Metcalfe 2012).

The advantage of portraying this relationship as a continuum is that it highlights that many aspects of measurement fall somewhere in between the two ends of the spectrum. In practice, few measurement approaches are entirely subjective or objective in nature: choice of objective indicators is often informed by bottom-up community consultations and piloting; subjective-evaluations are often worded and grouped according to objectively-defined definitions of resilience (Jones 2019). As such, we are careful to make distinctions between the two categories of definition and measurement when referring to the properties of measures used in our survey.

2.3. A SURVEY COMPARING OBJECTIVE AND SUBJECTIVE-MEASURES OF RESILIENCE

In order to shed light on the relationship between objective and subjectively-evaluated resilience, we carry out a representative survey of 2,380 households in the Karamoja region of Northern Uganda. We assign separate RIMA and SERS modules to each household allowing like-for-like comparisons of both approaches. Below we provide further detail on how RIMA and SERS scores are computed, as well as the survey methods used to inform our analysis.

2.3.1. RIMA: an objectively-evaluated resilience module

The body of objective measures for resilience measurement is large and ever-growing (Schipper and Langston 2015; Bahadur and Pichon 2016). Amongst them, one of the most commonly applied quantitative measures is the Resilience Index Measurement Analysis (RIMA). RIMA is developed by the United Nations Food and Agriculture Organisation (FAO) and has undergone a number of iterations since its development by Alinovi et al. (2008) as an econometric model for estimating household-level resilience to food security. Its latest iteration, RIMA-II, comprises a multi-dimensional index devised through Structure Equation Modelling (SEM) and designed to reflect food security outcomes (FAO 2016).

In terms of how RIMA-II conceptualises resilience, the approach acknowledges frameworks supported by the Technical Working Group on Resilience Measurement (FSIN 2014a). It unpacks resilience into four "pillars":

(1) **Access to basic services**: a household's access to enabling institutional and public services environments. It includes indicators like health facilities; education; credits; water; and other basic services.

(2) **Assets**: 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 assets.

(3) **Social safety nets**: the network upon which a household can rely on when faced with a shock. It includes both formal and informal transfers; as well as social networks.

(4) **Adaptive capacity**: a "household's ability to adapt to the changing environment in which it operates" (FAO 2016, p. 14). It includes factors such as education; number of income sources; and 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 3).

Table 3: 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 used format, RIMA-II is estimated via a two-step procedure. First, a factor analysis is performed with indicators for the four RIMA pillars. Second, a Resilience Capacity Index is devised. This is done by combining the output of the factor analysis with 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 variables) 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 and commonly associated with wellbeing-related outcomes. 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). An annotated diagram of processes employed in devising the RIMA-II score is represented in Appendix A Figure 21. For full details of the procedure see FAO (2016) and D'Errico et al. (2017).

For the purposes of this paper, we also introduce an alternative specification of the RIMA-II model. This hybrid model – which we refer to henceforth as 'RIMA' – removes the score's tie to a food security outcome. Our hybrid RIMA measure follows the same initial steps as the original RIMA-II and is based on the conceptual premises outlined in the RIMA-II's guidelines (see FAO 2016 and D'Errico et al. 2017). It uses the same four pillars of resilience, and includes all of the indicators used in RIMA-II. The only difference is that it does not include the wellbeing out part of the structural equation model. As per the original RIMA-II approach, RIMA scores are normalised on a scale of 0-1.

The main advantage of this new model is that it better reflects resilience to broader livelihood outcomes (i.e. overall resilience), rather than their ability to solely maintain food security outcomes (the focus of the original RIMA-II model). As such, this hybrid version of RIMA is better suited for comparison with the SERS model which is similarly focused on a multi-hazard view of resilience. We therefore consider it our preferred specification for the paper's main analyses. However, we also recognize the well-established use and track-record of the RIMA-II method and run parallel analyses comparing SERS with the original RIMA-II approach (see Section 2.3.4. Testing Assumptions, and Appendix A Table 14).

2.3.2. SERS: a subjectively-evaluated resilience module

For the subjective module of our survey we use the Subjectively self-Evaluated Resilience Score (henceforth referred to as SERS). Similar to RIMA, SERS considers resilience to be made up of a range of resilience-related capacities. The module is adapted from a hazard-specific variant proposed by Jones et al. (2018b) and features a total of nine resilience-related capacities and capitals chosen on the basis of an extensive review of available literature (see Table 3). Each resilience-related capacity is then adapted to self-elicited questions, with respondents asked to rate their levels of agreement ranging from strongly agree to strongly disagree. Pilot exercises of the module were carried out in a nationally representative survey of Kenya (early 2017) and regional surveys in Hpa An, Myanmar (Jones 2018a) helping to inform question wording and composition.

Table 4: List of nine resilience-related capacity questions used in the SERS module

Resilience-related capacity	Question	References
Absorptive capacity	Your household can bounce back from any challenge that life throws at it	Béné et al. (2012) Bahadur et al. (2015)
Transformative capacity[7]	During times of hardship, your household can change its primary income or source of livelihood if needed	Béné et al. (2012) Kates et al. (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)

Subjectivity is at the core of the SERS approach. However, it is important to note that by prescribing a set of resilience-related characteristics, SERS falls under the category of objectively-defined (i.e. characteristics are selected from a review of the wider resilience literature, rather than those being measured 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. Respondents are asked to score their level of agreement with each capacity using a Likert scale with five response items (Strongly disagree = 1, Strong agree = 5). While numerical conversion of Likert

[7] The definition of transformation used here is largely based around the ability of a household to modify livelihood activities when and if required (Béné et al. 2012; Kates et al. 2012). However, we recognise that the term has many different interpretations. Others draw heavier emphasis on power dynamics and agency (see Carr 2019). As with all capacity questions, we recognize the limitations of short and easy-to-interpret statements and encourage others to tailor SERS to fit different capacity definitions.

scale responses of this type is typical across the social sciences, it is also important to recognise that assumptions of cardinal comparability are disputed (Kristofferson, 2017).

Each characteristic can either be compared individually or aggregated together to form a single collective score comprised of multiple capacities. Together this aggregate score constitutes the household's resilience outcome, acting as a rough marker of overall resilience. A Cronbach's Alpha score of 0.79 suggests high internal consistency across the nine resilience-capacities. To ensure computational ease and transparency, we numerically convert answers for each of the resilience-related capacity questions and calculate an equally-weighted mean score. As with the 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, 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 2.3.4 Testing Assumptions and Appendix A Section 1).

SERS is designed to be flexible with regards to different definitions and characterisations of resilience. As such, it allows evaluators to pick and choose any combination of resilience-related capacities. In this paper, our main model uses all nine resilience-related capacities based on the approach used by Jones (2018a). However, we also look at different variants of SERS based on widely used frameworks in the resilience literature. The first is a subset of three resilience-capacities comprising Absorptive, Adaptive and Transformative capacities, which we name the 'AAT' variant. This combination of capacities has been widely applied within the resilience literature (Pelling 2010; Béné et al. 2012) as well as shaping resilience-building programmes – see Oxfam's Framework for resilient development (Jeans 2017). On the one hand it builds on early socio-ecological concepts of resilience, highlight the ability of system to maintain core functions in response to threats (Holling 1973; Walker et al. 1981). On the other, it acknowledges the importance of adaptation, and in some cases transformation, to allow systems to deal with evolving risk (Kates et al. 2012).

A second version uses another subset of three capacities made up of anticipatory, absorptive and adaptive capacities, named the '3A' variant. This mimics the 3As framework first proposed by Bahadur et al. (2015) and used by the BRACED programme as well as range of other assessments (Wilson & Yarron 2016; Bottazzi et al. 2018). This framework is similar to the AAT model, adding particular weight to the importance of anticipatory mechanisms, such as early warning systems and disaster risk reduction activities (in place of transformation) (Thomalla & Larsen 2010).

Lastly, as noted in Section 2, we focus our SERS module on a multi-risk view of resilience. As such, SERS questions make no reference to individual hazards. Instead we refer generically to 'threats', 'challenges' or 'disasters'. Doing so is also important in minimising the likelihood of priming effects amongst respondents (OECD 2013). However, we recognise that specifying resilience to single hazards can also be of benefit to practitioners – particularly in cases where interventions target a single hazard. Accordingly, we also include a hazard-specific SERS module mimicking the example used by Jones et al. (2018a) and focused on drought risk – the primary threat facing livelihoods in Karamoja (see Appendix A Table 3 for wording).

Inherently the questions used in the SERS module cannot cover all aspects of resilience, nor do they seek to. Rather, they give a useful indication of a subset of capacities that are known to strongly influence a household's resilience. In addition, while each capacity is considered distinct in its own right, it is important to note that some degree of overlap is inherent, limiting the extent to which the unique contributions of each can be isolated. For example, close ties exist between adaptive and transformative capacities, as both relate to processes of structural change (Few et al. 2017). Yet, these are often referred to separately within the resilience literature (Pelling 2010; Kates et al. 2010). As outlined above, different subsets of the SERS module can also be constructed to account for an evaluator's preferred definition of resilience.

Finally, we note that reasons for quantifying subjective-evaluations of resilience may not be altogether obvious. Subjective insights on resilience have been gathered extensively through qualitative means, recognising the richness and nuance that these methods provide (Ayeb-Karlsson et al 2016; Maxwell et al. 2015). SERS is by no means an attempt to replace the importance of qualitative contributions to our understanding of resilience through interviews, focus groups and immersive research methods. Rather, it seeks to complement it. It is a way of translating bottom-up subjective judgements into a quantifiable metric that can be readily compared, and potentially combined, with traditional objective approaches. In doing so, it answers recent calls for greater diversity of research methods in understanding resilience:

> '*Resilience measurement requires multiple method assessment approaches that capture perceptions, opinions, judgments and the nature of social interactions as well as the observable or easily measurable characteristics of social ecological systems'.* Maxwell et al. (2015:4)

2.3.3. Data

To test the relationship between objective and subjectively evaluated resilience we make use of a household survey conducted in Karamoja, Uganda in 2016. The primary purpose of the survey was to understand the resilience capacities of communities in Karamoja to determine baseline values for an upcoming impact evaluation[8].

The survey is composed of a total of 2,380 households. The sampling strategy is stratified according to the five strata: (1) target households, which are those reached by FAO's

[8] For more information on the types of activities supported by FAO in Karamoja and the broader evaluation see http://www.fao.org/3/ca0345en/CA0345EN.pdf. A follow-up survey is scheduled to take place in late 2020 resulting in a panel dataset.

activities in 12 parishes of the Moroto and Napak districts; (2) direct spillover households, which are those located in the neighbouring parishes of Moroto and Napak districts but not affected by FAO interventions; (3) indirect spillover households, which are those unaffected by the project in 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 (the principle ethnic group in the region); (5) and the pure control group, comprised of households located in the Kaabong district, which have the same ethnic group and socioeconomic conditions as the target group, but which are not involved in the FAO programme.

For the purposes of this survey, we do not make use of the distinct strata in analysing our results and pool all responses together. However, we hope to exploit results from the different groups in follow up research to test the impacts of FAO activities on resilience outcomes.

The household questionnaire was comprised of a range of thematic sections and piloted in Moroto district in November 2016. Specifically, it collects detailed information on household characteristics, including: food and non-food consumption; perceived shocks; coping strategies; as well as the two respective resilience modules (in the form of SERS and RIMA). Results from the survey are shown below.

2.4. RESULTS

The first research question that we explore is how objectively- and subjectively-evaluated measures of resilience compare. Figure 4 shows a series of associations comparing RIMA and SERS outcomes. The first thing to note is that the distribution of scores is far narrower for RIMA ($s = 0.13$, $\bar{x} = 0.31$) than for SERS ($s = 0.21$, $\bar{x} = 0.49$) (Figure 4a).

Figure 4: Densities and relationships between RIMA and SERS variants

Notes: Panel a shows probability densities of our hybrid RIMA model alongside the SERS (9C variant). Panel b features a count plot between SERS scores and RIMA values rounded to match the same number of permittable response items as SERS (33). Panels b, c, and d feature mean SERS scores for aggregated RIMA values rounded to the nearest 0.1.

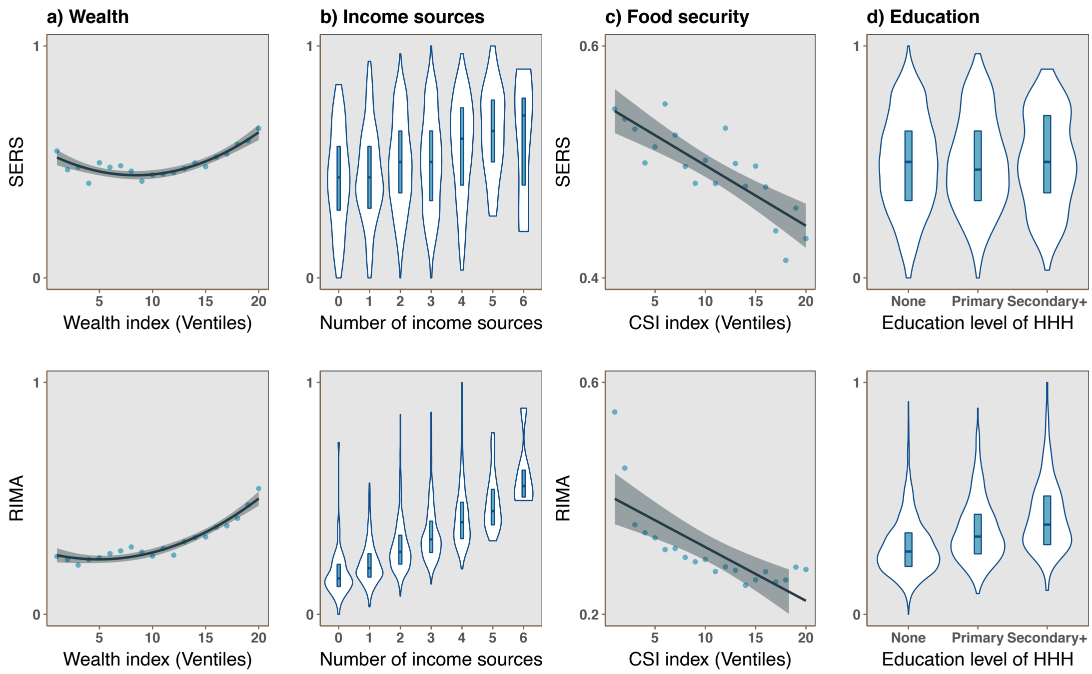
Secondly, the association between RIMA and SERS scores is positive. Figure 4b shows a count plot of the full range of resilience scores, while Figures 4c-d show mean SERS scores for aggregated RIMA values. While the raw values are somewhat scattered (R^2 = 0.25), a relatively clear linear relationship is apparent not only for the full SERS model, but the SERS-3A variant as well. Values do not quite line up 1:1, with SERS tracking slightly higher for low RIMA values and slightly lower for high RIMA values.

We are also interested in comparing associations between the two resilience modules and key socio-economic 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 RIMA and SERS modules demonstrate positive relationships (as shown in Figure 5a), with higher wealth accumulation 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[9]). Both have traditionally been considered as core drivers of resilience at the household level (Adger 1999; Jabeen 2010). Not all assumed associations overlap however. For example, while the highest level of education for

[9] 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 is declining or improving (see Maxwell et al. 2003)

household heads shows a marked positive association under RIMA, no such association is apparent for the SERS module[10].

Figure 5: Relationships between objective and subjectively-evaluated modules and key socio-economic variables



Notes: Panels a) and c) feature mean SERS and RIMA scores across binned ventiles. Plots b) and d) feature violin plots with a boxplot (median and first/third quartiles) in the centre and kernel probability densities along the outside.

While descriptive and bivariate analysis is useful in uncovering broad associations, it is also important to account for the effects of any confounding factors before drawing firm conclusions. To do so we run a series of OLS regressions with SERS and RIMA as dependent variables. A range of socio-economic traits – 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 cluster-robust standard errors 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 Robustness Checks.

10 We return to the relationship between education and resilience in more depth in Section 2.4

$$SERS_{hc} = \alpha_c + \beta_1 SHOCK_{hc} + \beta_2 DRIVER_{hc} + e_{hc} \quad (1)$$

The primary OLS set up with area-fixed effects is presented in Equation 1. Here the outcome $SERS_{hc}$ 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. These include drought, flood, crop disease and illness. $DRIVER_{hc}$ is a vector of socio-economic variables commonly associated with drivers of household resilience. α_c is shown as a sub-county fixed effect (expressed as dummies) with the error term represented by e_{hc}.

Outputs from the above are compared directly with Equation 2. This model shares an identical structure to that of Equation 1, simply replacing SERS with RIMA (through $RIMA_{hc}$) as the outcome variable of interest.

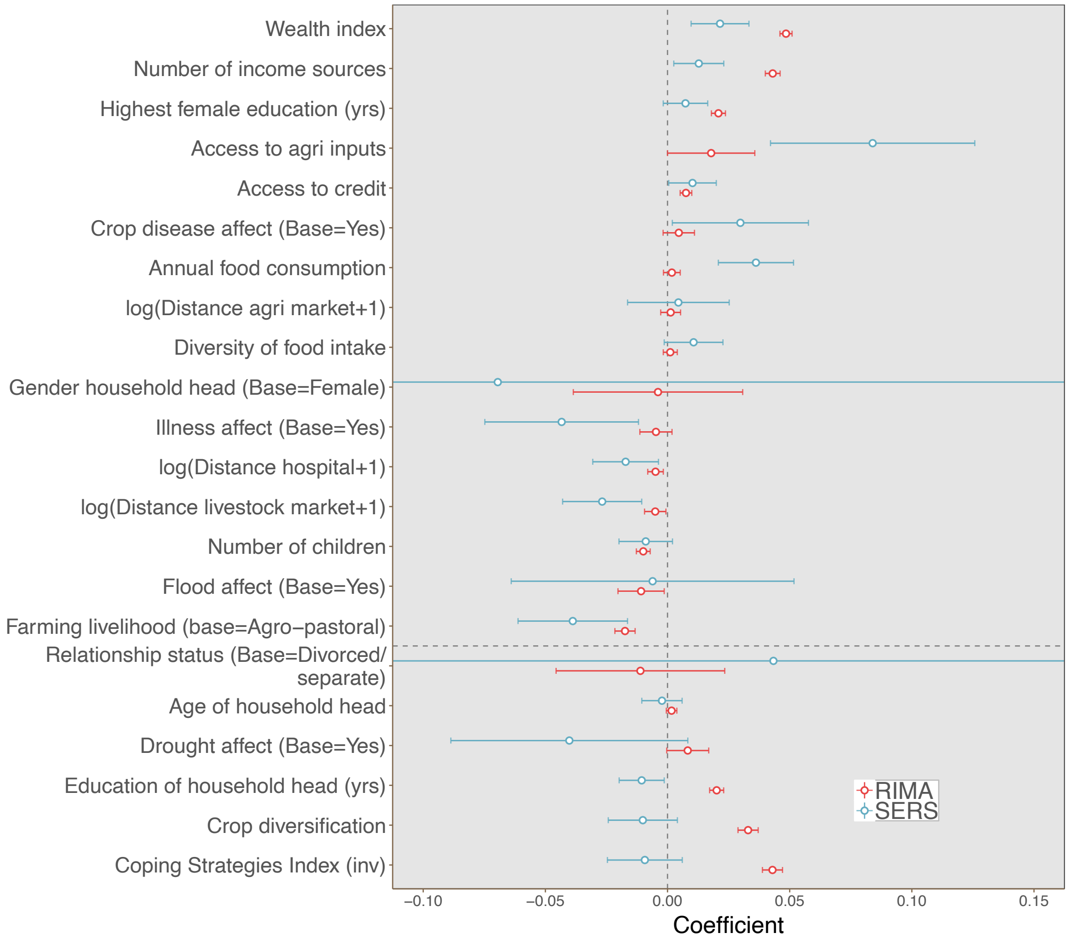
$$RIMA_{hc} = \alpha_c + \beta_1 SHOCK_{hc} + \beta_2 DRIVER_{hc} + e_{hc} \quad (2)$$

In effect, outputs from Equation 2 are largely uninteresting in isolation: results simply inform us of the assumptions and weights assigned to various indicators that feed into the RIMA model. Instead, real utility comes from side-by-side comparisons of Equations 1 and 2.

Given that the SERS approach does not factor any of the shocks or input variables when asking people to self-evaluate, a comparison of the two models serves as a quasi-independent check of the RIMA set-up (and indicators used within). 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. In practice, it is difficult to argue that RIMA and SERS are capturing the same latent construct (i.e. overall household resilience). However, they overlap considerably and should be expected to broadly reflect the same associations with relevant drivers of resilience.

Figure 6 presents side-by-side comparisons of outputs from the RIMA and SERS models. Variables above the dashed horizontal line share the same sign of association for both models (i.e. a positive or a negative association on resilience), those below have opposing signs. For ease of viewing and interpretation, variables are ordered in relation to the highest and lowest coefficients in the RIMA model (essentially showing us the magnitude of relative weightings used in the RIMA set up). Given the potential for non-linear relationships we also include quadratic terms for each of the socio-economic drivers (see Appendix A Table 17). Again, many associations are matched between the two approaches – though there are some differences between linear and non-linear relationships (notably wealth and CSI).

Figure 6: Coefficient plot comparing associations with socio-economic drivers of resilience



Notes: Dots represent standardised beta coefficients, 95% confidence intervals are represented as whiskers. Whiskers for gender and relationship status variables under the SERS model have been cut-off for ease of comparative viewing. Standard errors are clustered at the sub-county level. The horizontal dashed line represents variables that disagree in sign between RIMA and SERS models (those above agree in sign; those below do not). Variables are ordered in relation to highest-to-lowest coefficients for the RIMA model (the opposite is the case for variables below the dashed horizontal line)

Another way to compare our two resilience modules is to see whether the individual characteristics of RIMA's resilience model are associated with SERS. RIMA breaks resilience down into four core characteristics: adaptive capacity; assets; social safety nets; and access to basic services. To examine the extent to which these characteristics are reflected in people's self-evaluations we run an OLS model (Equation 3) with SERS as the outcome variable, $SERS_{hc}$. As with prior models, we include area-fixed effects and cluster standard errors at the sub-county level. Under this specification each of RIMA's four characteristics[11] are represented by AST_{hc} (assets), ABS_{hc} (access to basic services), SSN_{hc} (social safety nets) and AC_{hc} (adaptive capacity) - see FAO 2016 and D'Errico et al. 2017 for a full list of indicators associated with each pillar.

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

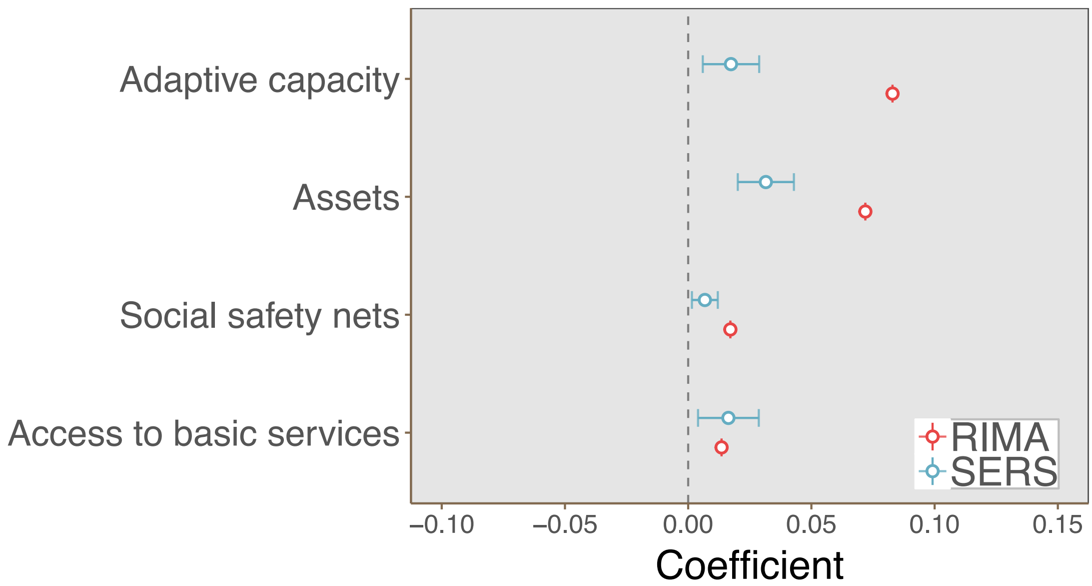
$$SERS_{hc} = \alpha_c + \beta_1 AST_{hc} + \beta_2 ABS_{hc} + \beta_3 SSN_{hc} + \beta_4 AC_{hc} + e_{hc} \quad (3)$$

Outputs from Equation 3 are compared directly with a parallel model that places RIMA scores, *RIMA*$_{hc}$, as the outcome variable. Indeed, given that the indicators used in compiling RIMA's four pillars are largely independent of the SERS set-up it can loosely be considered as an independent check.

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

Again, Equation 4 on its own is not particularly informative. It demonstrates the weightings assigned to each of four characteristics of resilience as specified within the RIMA model (and hence why the confidence intervals are far smaller for RIMA compared with SERS outcomes). However, when comparing Equations 3 and 4 together we see that all four characteristics are positively associated with SERS (Figure 7). Assets have the largest marginal effect with social safety nets the lowest. It is also worth noting that the effect sizes for anticipatory capacity and assets are far higher for the RIMA model compared with SERS. While this may imply that RIMA is overweighting, it's important to consider that self-evaluations have a far wider range of potential influencing factors when compared with RIMA's four characteristics.

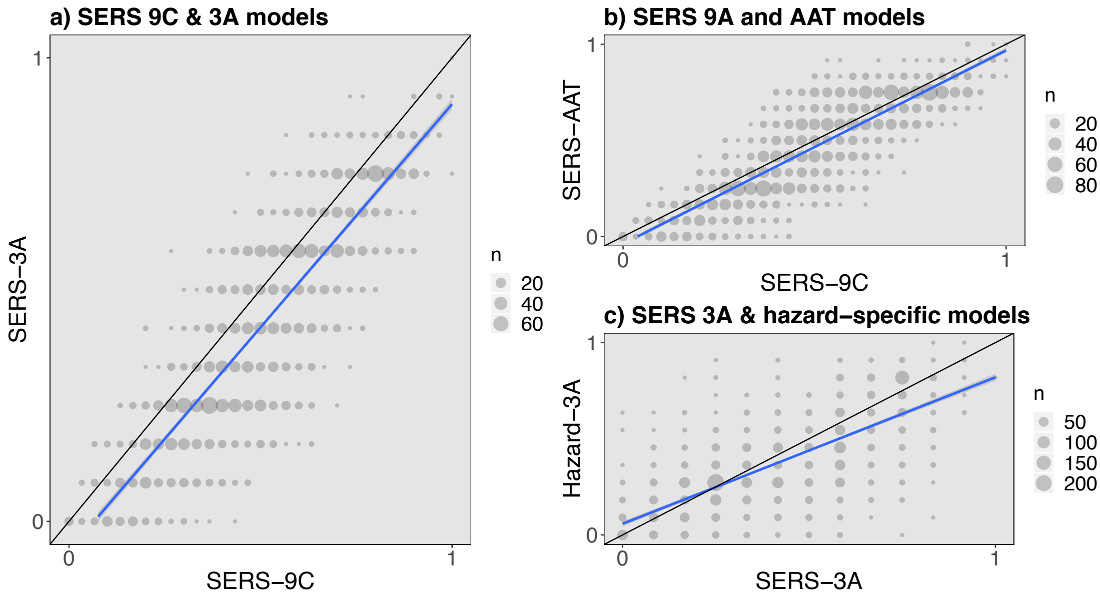
Figure 7: Coefficient plots showing associations between RIMA (blue) and SERS (red) relative to RIMA's four characteristics of resilience



Notes: Dots represent standardised beta coefficients, 95% confidence intervals are represented as whiskers. Standard errors are clustered at sub-county level.

The paper's final research query seeks to compare outcomes of different versions of the SERS approach. As is clear from Figure 8a, strong overlaps exist between the 9C and 3A variants of the SERS model, with both closely tracking a 1:1 ratio. A similar association is also apparent when comparing 9C and AAT variants in Figure 8b. While values are more scattered, comparison of the 3A model of overall resilience with the 3A hazard-specific variant also demonstrates a high degree of overlap.

Figure 8: Count plots of relationship between different variants of self-evaluated resilience

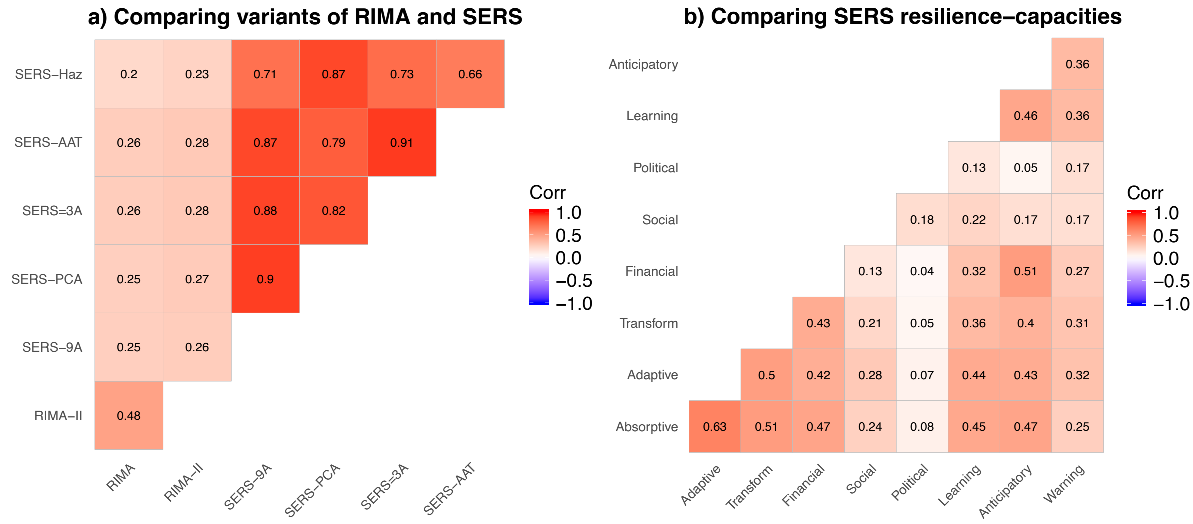


The size of dots represents the frequency of responses with the same score. The black line follows a direct 1:1 ratio between the two measures. The blue line shows a liner regression line of best fit. Note that all models in Figures a) and b) are in relation to overall resilience, Figure c) compares a model of overall resilience with a hazard-specific model (focused on drought).

Figure 9a shows that correlation coefficients between SERS variants are high. By way of an interesting point of comparison, the relationship between the original RIMA-II specification (the variant of RIMA that is tagged specifically to a food security outcome) and our hybrid version of RIMA (which has no outcome variable and is therefore a better reflection of overall resilience) is notably weaker with an R^2 of 0.48.

We can also look at correlations between the various resilience-related capacities that contribute to SERS. Figure 9b highlights a wide range of associations, with the strongest tie appearing to be between Adaptive and Absorptive capacities. To get a more detailed understanding of the links between resilience-related capacities we also run a Principal Component Analysis with all nine capacities in the full SERS module. Appendix A Table 12 confirms that Absorptive and Adaptive capacities are the two strong contributors to the SERS scores, followed by Anticipatory and Transformative capacities. Interestingly, Political capacity appears to have consistently low correlations with other resilience-related capacities, with slight loadings in the first principal component. As such, its use is dropped as part of the SERS-PCA variant, weighted on the basis of the first principal component across all nine-capacities (see Appendix A Table 12).

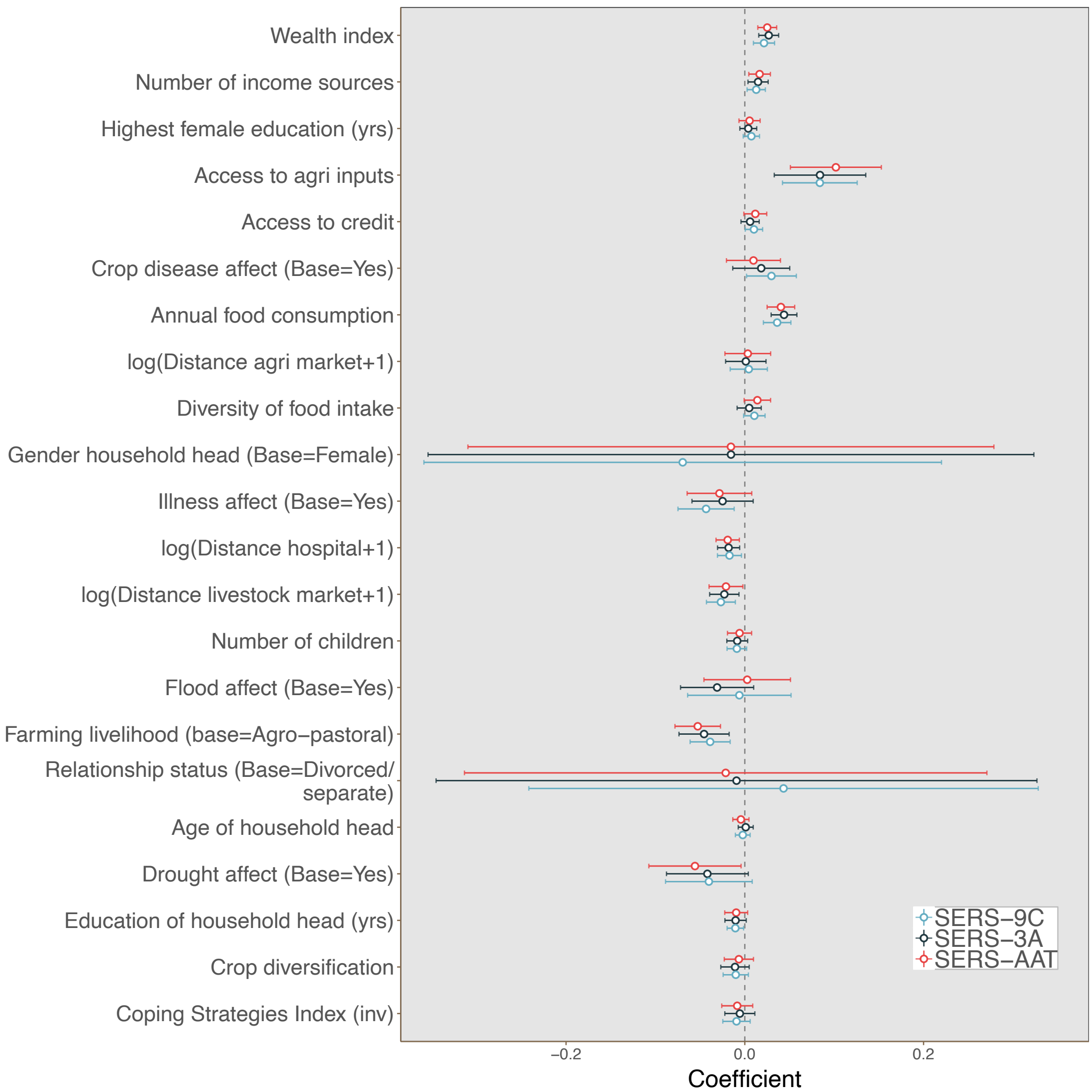
Figure 9: Correlation matrix of different resilience modules and SERS resilience-capacities



Notes: Correlation plots shows coefficients for various SERS traits with corresponding values matched to colours in the legend. Correlations are presented as Pearson coefficients.

While different subjective variants appear to be highly correlated, what about similarities between underlying socio-economic 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 the 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 Figure 10, associations between subjective self-evaluations of resilience and various drivers and shocks remain notably similar across the three variants (see also Appendix A Table 16). Indeed, there are only a small number of variables that do not exhibit the same sign and level of statistical significance.

Figure 10: Coefficient plot comparing different variants of the SERS subjectively-evaluated resilience model



Notes: Dots represent standardised beta coefficients, 95% confidence intervals are represented as whiskers. Standard errors are clustered at sub-county level.

2.3.4 Testing assumptions and robustness

In order to test the validity of the paper's findings we perform a number of robustness checks. Appendix A Table 13 shows comparisons of 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 our preferred model setup) 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 largely consistent.

Another important step taken in our analysis is the use of a modified version of the RIMA approach. The hybrid RIMA model is considered a more suitable comparison with SERS given that 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 too (not just food security). Therefore, we run the same model set-ups as before, using the original RIMA-II instead of a hybrid version. Results are presented in Appendix A Table 14 with a similar range of regression runs as specified in Appendix A Table 13. 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.

A key factor in evaluating survey modules with multiple components is weightings. While we use an equally weighted average for most of the results presented in the paper, we also test our results with an alternative version (labelled SERS-PCA) that weights resilience-capacities according to the first principal component (with 8 questions retained). Accordingly, Appendix A Table 15 re-runs comparisons between RIMA and SERS-PCA. Again, we find few differences.

Lastly, we note that a weakness of many subjective measures is a tendency for respondents to agree with all questions, or provide consistently 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 Appendix A Table 16).

2.4 DISCUSSIONS AND CONCLUSION

Results from our Karamoja survey point to a number of interesting findings and discussion points. Below we reflect on our three main research areas. We also consider limitations and ways forward for future efforts to define, measure and promote resilience.

2.4.1. Comparing objective- and subjectively-evaluated resilience

One of our main findings is that a positive linear relationship exists between the objectively- and subjectively-evaluated modules used in our Karamoja survey. This relationship is clearly highlighted in Figures 4c-d, with mean SERS scores consistently rising with higher aggregated RIMA values. The fact that two largely independent approaches point in a similar direction will give some confidence to resilience evaluators. More importantly, the association suggests that, in the case of Northern Uganda, households that are assumed to be resilient (at least from the perspective of FAO's criteria) generally perceive themselves to be resilient as well.

Another point is abundantly clear: the relationship between RIMA and SERS is not especially strong. An R^2 of 0.25 suggests that any correlation is moderate at best, and that the two measures should not necessarily be used interchangeably. The implications for resilience measurement depend on how the scores are used and compared. From one perspective, comparing raw scores paints a picture of a noisy relationship between subjective and objective-measures (Figure 4b); from another, aggregated information shows neat and clear trends (Figures 4c-d).

Differences in the distribution of both scores are also marked, with standard deviations (*s)* of 0.21 and 0.13 for SERS and RIMA respectively. The finding suggests that, from the perspective of people's own judgements, levels of resilience are far more varied than those assumed under RIMA. Part of this may reflect the fact that subjective-evaluations place no limits on the wide range of factors that an individual might consider in evaluating their household's resilience – as opposed to RIMA that is constrained to a handful of objective indicators. It may also reflect a diversity of subjective interpretations and judgements on resilience.

With this in mind, it is worth reinstating that neither RIMA nor SERS are direct measures of a household's resilience. They are two different ways of inferring it. Understanding which of the two most closely approximates a household's 'true' resilience also requires tracking changes in wellbeing outcomes over time – itself subjective to different interpretations and inferences. As such, the value of both measures should be considered equivalently, based on the strengths of methodological assumptions and objectives of the evaluator. Our findings underscore the need for development actors to be mindful of the diversity of knowledge sources for resilience (Knippenberg et al. 2019). Care should also be taking in assuming that aggregated resilience outcomes are homogenous across communities and households. Most importantly, as evaluators seek to refine and choose methods for evaluating development practices, it is imperative that the merits and limitations of different methods are made fully transparent.

2.4.2 Comparing associations with drivers of household resilience

The second dimension of our study looks at whether objective and subjectively-evaluated approaches share similar associations with key socio-economic drivers of resilience. Like-for-like comparisons in Figures 5 and 6 show that most of the traits in our model (16 out of 22 variables) share the same sign of influence for both RIMA and SERS. Common significant drivers include: asset-wealth; diversification of income sources; livelihood type; distances to a hospital and livestock market; and access to agricultural inputs and access to credit. Most of these have a rich history of association with resilience within the academic literature (Tyler & Moench 2012; Cutter et al. 2008; Adger 1999; Jabeen 2010).

Many of the associations make logical and conceptual sense. For example, the importance of wealth and financial capitals is well documented as a driver of resilience, allowing households to accumulate and use assets during times of hardship (Tyler & Moench 2012; Cutter et al. 2008). The same is true for income diversity, where development practitioners have long promoted diversity as a means of spreading risk (Jabeen 2010). A negative association with distances to hospitals and markets is also reassuring, though it's important to note that both are largely found in urban areas and may be confounded by other unobserved variables.

Interestingly households reliant on farming as their primary source of livelihood appear to have lower scores than agro-pastoralists. This 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 (or 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. Many development actors have historically portrayed nomadic pastoralism as a particularly vulnerable and unviable source of livelihood in the region (Levine 2010).

Strong overlaps in association suggest that SERS is picking up on many of the same socio-economic drivers and indicators used in deriving the RIMA model. The fact that all four pillars of the RIMA model are positively associated with SERS outcomes further underscores this point (Figure 7). Common associations are all the more significant as the two modules are largely independent of one another. None of the objective indicators that make up the RIMA model are used in SERS. 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 survey module this would be a considerable undertaking.

However, the two modules do not agree on associations amongst all drivers. Indeed, just as much can be learned from disagreements between the objective and subjective measures. For a start, effect sizes differ markedly. For example, wealth has the strongest positive association with RIMA (a 0.048 rise for every one standard deviation increase in the wealth index). Yet, its effect on SERS is less than half (a 0.021 rise). The implication here is that while both RIMA and SERS recognise wealth as an important component of resilience, its association is considerably lower when considering people's own self-evaluations. Similar patterns are true for other drivers, including diversity of income sources and years of schooling for female household members – both of which have significant positive associations, though with far weaker effects on SERS outcomes.

Interestingly, the converse is also true. A number of traits have far stronger effect sizes for SERS than for RIMA. Most notable are large differences for access to agricultural inputs and livelihood practices, with SERS coefficient values twice those for RIMA. Some drivers are significantly linked with one approach and not the other. For example, food consumption has a significant positive association with RIMA, with a negligible and insignificant role for SERS outcomes. Again, the implication being that the influence on socio-economic drivers of resilience differs from the perspective of expert elicitation (i.e. RIMA) compared with people's own subjective judgements (SERS).

Perhaps the most important finding relates to instances where drivers have opposing signs of influence (those below the grey dotted line in Figure 6). Here we observe traits that have fundamentally different associations between RIMA and SERS approaches. The largest such difference comes in the form of the Coping Strategies Index, considered a proxy for food insecurity. CSI has a large positive link with RIMA (households that are more food secure have higher RIMA scores). Yet, its association with SERS is not statistically significant. If anything, the sign of influence is slightly negative. Appendix A Table 17 also suggests the relationships may be non-linear, with opposing signs for quadratic terms. We would, however, caution against the blanket conclusion that food security plays a negative (or no) role in people's subjective judgements. Indeed, annual food consumption, diversity of food intake and access to agricultural inputs all have strong positive associations with resilience (far higher than for RIMA in fact). Rather, it highlights that food security is multi-faceted, and that different elements are likely to interact with resilience in different ways. Our findings may also suggest the need for greater evidence and clarity in the heavy use of CSI as a proxy or food security in weighting objective models.

Another interesting disparity relates to the role of education. Higher education levels of the household head have strong positive associations with RIMA. This is reflected in the wider resilience literature where higher education is linked with individual-level behaviours supportive of resilience and heightened awareness of future risk (Pissello et al. 2017). Yet, surprisingly, we find that education has a slight negative association with SERS. This may again reflect differences in judgement between subjective and objective measures. However, we believe that geography and context may also be playing a strong role here.

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 likely 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); Béné et al. 2016a; and Claire et al. (2018). Together this suggests that greater understanding of the links between education and household resilience is needed before strong conclusions can be drawn. More can also be done to distinguish between the roles of formal and informal education in supporting resilience, including how they are reflected in resilience metrics.

Lastly, we consider the role of past shocks. It is commonly assumed that exposure to shock will reduce a household's resilience capacities, as over time repeated shocks wear away at a household's ability to deal with future risk (Silbert & Useche 2012; Kahn 2005; Ibarraran et al. 2009). However, findings from the Karamoja survey suggest that this relationship may be more nuanced. Households that have not experienced a shock in the last 12 months are associated with lower SERS scores than those that have experienced a shock. This trend runs true across a number of shock types, including droughts, floods and illness (not so for crop diseases).

While the relationships may seem somewhat counterintuitive, there are conceptual and practical grounds to consider it. Households that have experienced a recent shock may be in a better position to not only gain insights into relevant coping strategies, but better anticipate and adapt to future risks using the experiences gained in recovery (Berkes and Turner 2006). Experiential grounding, with knowledge built up through experience of past shocks to inform more effective future strategies is well documented (Tschakert & Dietrich 2010). Though we strongly suspect that any such advantages would only accrue in the context of smaller shocks or stresses; it is harder to see how acute threats would be advantageous. Indeed, this may partially explain why crop disease shows an opposing trend, as Karamoja has a long history of devastating locust outbreaks and disease-related threats (Gartrell 1985). Though this trait is difficult to verify without follow-up research.

We also consider that changes in risk perceptions may be a factor, with the wider literature mixed on this issue. Wachinger et al. (2013) highlight examples such as Ruin et al. (2007), Ming-Chou (2008), and Mirceli et al. (2008) that show how direct experience of a natural hazard leads 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 beliefs that future events are unlikely to affect people and thus lower risk perception. Given the consistency of negative associations for SERS across a range of shocks, we see sufficient grounds to challenge many objective approaches (including RIMA) in being explicit in assumed links between prior shocks and resilience.

Above all, our findings point to the importance of recognising different sources of knowledge on resilience. The fact that associations with many socio-economic drivers overlap between SERS and RIMA is certainly encouraging. Again, it suggests that both modules are picking up on similar underlying properties. However, the extent (and in some cases the sign) of some associations clearly differ between objective and subjectively-evaluated modules. In such instances, it is important for evaluators to rigorously examine the evidence base for key assumptions. It also calls for a plurality of knowledge sources to be considered. This is particularly relevant for picking indicators that feed into objective measures.

2.4.3 Different variants of the SERS subjective approach point in the same direction

Our final research question looks at how different variants of the SERS module compare. Figure 8 shows that all three variants (3A, AAT and 9C) of the SERS model are highly correlated. The same is also true in comparing versions of SERS that focus on hazard-specific and overall resilience (see Figure 9). We believe that these traits have important implications for how resilience is characterised. To date, resilience can (and has) been chopped up in myriad ways (as alluded to in Section 2). In fact, considerable time is spent arguing over the right mix of capacities constituting a resilient social system: whether adaptation is needed to recognise evolving risks (Marshall et al. 2010); whether transformation features, even if systems have radically altered (Pelling 2010; Béné et al.

2012); and whether a whole host of other capacities and capitals, such a learning or anticipating, play distinct roles (Tschakert & Dietrich 2010; Bahadur et al. 2015).

An assumption therefore prevails that an evaluative tool's choice of resilience-capacities will have considerable implications for measured outcomes. Yet, by comparing two popular resilience frameworks (3A and AAT), as well as a much larger set of 9 resilience-related capacities drawn across the wider literature (9C), we find very similar results. This applies both to correlations between them as well as associations with key socio-economic drivers (Figure 10). Interestingly, the fact that Absorptive, Adaptive, Anticipatory and Transformative have the highest loadings in the first principal component of the PCA suggests that the resilience literature may be pointing in the right direction (and that differences between the mix of these four are of little importance). Of course, the limitations of subjectively-evaluated measures, and the potential for the influence of known biases, have to be considered. However, these findings present a challenge to lengthy debates over the exact composition of resilience-related capacities (Bahadur and Pichon 2017). It may also lessen the burden placed on choosing the 'right' mix of resilience-related capacities used in measurement approaches – whether subjective or objectively-oriented.

Our findings also suggest that outcomes from shorter SERS modules largely mimic those in the full range of resilience-related capacities. This is of critical importance in efforts to save survey space and reduce the time needed in interviewing households. As pressure grows on resilience evaluators to design tools that are ever cheaper and quicker to administer (Tiwari et al. 2013), we believe that short subjectively-evaluated modules offer some promise.

2.4.4 Limitations and routes forward

In reflecting on the implications of our findings, we highlight a number of important considerations. Firstly, we reiterate that neither RIMA nor SERS should be interpreted as 'true' measures of resilience. They are both indirect attempts at approximating a household's resilience, with no means of validating either without continually tracking wellbeing over time. Instead, our findings highlight the importance of diversity in sources of knowledge for resilience. Having said that, we are reassured to see that two largely independent ways of measuring resilience show moderate correlations, and that our subjective measure is associated with many of the same socio-economic drivers. To be clear, this largely infers that SERS outcomes are closely associated with the indicators used in the RIMA model (as the socio-economic drivers chosen here largely match those used in formulating RIMA). The fact that other drivers differ entirely in terms of sign and significance also provides helpful impetus: challenging evaluators to re-examine long-held assumptions, and encouraging evidence-based selection of indicators.

As with any one-off survey, findings should be interpreted with some caution. Given the subjective nature of the SERS module, a number of cognitive biases may be at play. For example, questions within the subjective module follow the same sequencing and may have resulted in cognitive fatigue or acquiescence bias. This is especially relevant given the strong overlap in wording of questions and response-items. In addition, both the overall and hazard-specific SERS modules were placed closely together in the survey. Respondents may therefore be primed in their responses. More needs to be done to explore the role of cognitive influences on subjective measures of resilience before firm conclusions can be drawn. Practices such as reverse coding of response-items and randomisation of question and module order may be important next steps.

More importantly, our findings point to the importance of encouraging resilience evaluators to be transparent about the merits and limitations of different approaches. For example, objectively-oriented measures (like RIMA) have the advantage of clear and comprehensive lists of standardised indicators. Yet, they struggle to account for factors that are not directly visible or tangible (Levine 2014). Though subjective tools are by no means a silver bullet, they prove an alternative solution by giving individuals the chance to factor 'softer' aspects such as social capital, entitlement and power into their internal judgements of resilience (Maxwell et al. 2015; Jones and Tanner 2017).

While some of these tradeoffs are relatively well known, others require further insights and careful research. One important question-mark for resilience measurement is how to deal with context-specificity (Zhou et al. 2010). Objectively-evaluated approaches tend to have fixed indicators and weights, meaning that two households are measured in exactly the same way. While this brings advantages of direct comparison, it does not account for the fact that the supporting traits of household resilience in one country might be completely different to those in another (Pelling 2010). Subjective measures don't rely on proxies, and as long as people view resilience in similar ways, should provide a valid way of comparing resilience across differing contexts. Sadly, the assumption of uniform views on resilience (just like happiness) is a large one, meaning that cross-cultural comparisons should be treated with caution (Ungar 2008; Selin 2012). Some methodological practices, such as anchoring vignettes, do however offer hope in this regard (King & Wand 2007).

We also see considerable potential for combining subjective and objective approaches. Building on the strengths of each approach, it is certainly possible to design measures that mix elements of both: whether matching subjective definitions with objective evaluations, or through combining the use of objective indicators with self-evaluations. Above all, we encourage evaluators to build on these findings, and capitalise on the advantages that both objective and subjective measures offer in promoting more diverse and comprehensive approaches to resilience measurement.

Chapter 3

Tracking changes in resilience and recovery after natural hazards

Insights from a high-frequency mobile-phone panel survey

Lindsey Jones and Paola Ballon

Knowing how resilience changes in the aftermath of a shock is crucial to targeting effective humanitarian responses. Yet, heavy reliance on face-to-face household surveys often means that post-disaster evaluations of resilience are costly, time-consuming and difficult to coordinate. As a result, most quantitative assessments are either carried out via one-off snapshots or by combining surveys conducted years apart. Doing so severely restricts our understanding of the temporal dynamics of resilience, particularly as it relates to inter- and intra-annual fluctuations.

In this paper we examine how household's resilience to multi-hazard risk changes over time. To do so we combine two novel approaches. Firstly, we use a high-frequency mobile-phone panel survey to conduct remote interviews in Eastern Myanmar. Surveys took place every six weeks over a one-year period. Secondly, we adapt a self-evaluated subjective measure of resilience to allow it to be readily administered via mobile phone. Shortly after the first survey was conducted, monsoonal flooding affected the site, allowing for the effects of flood exposure on resilience to be compared over time.

Our findings reveal how self-evaluated levels of resilience fluctuate considerably over the course of a year. To probe the effects of the monsoon floods, we compare resilience scores between households directly and indirectly affected by flooding. Scores drop sharply for the first three months amongst directly affected households, before slowly converging up to a year later. We also compare the effects of flood exposure on different socio-economic groups, revealing how female-headed households are particularly affected in the aftermath of flooding. Insights from the survey highlight the dangers of using one-off resilience surveys to measure resilience, and underscore the need for development actors to account for shorter-term changes in the design of resilience-building interventions. Lastly, our findings showcase the potential of methodological innovations in addressing some of the resource, time and logistical constraints of traditional resilience measurement practices.

3.1. INTRODUCTION

Tracking the resilience of households and communities is essential to ensuring that development and humanitarian resources are targeted at those most in need (Bahardur et al. 2015; Carter 2004). Unfortunately, accurately measuring resilience remains a critical challenge (FSIN 2014b; Levine 2014). Definitional and methodological ambiguities not only mean that resilience measurement is hotly contested (Alexander 2013), it contributes to the myriad of toolkits that have sprout in recent years. As such, many development actors have their own interpretations of what resilience is and how it should be measured (Schipper and Langston 2015).

Excessive data collection costs and the impracticalities of coordinating large household survey exercises mean that our understanding of resilience – at least when it comes to quantitative evaluations – is often restricted to snap-shots: one-off surveys carried out at a single point in time (Gregorowski et al. 2017; Platt, Brown & Hughes 2016; Jones 2018b). Little is therefore known about how a household's capacity to deal with risk evolves over shorter-term timescales – from days, to months to years (IFAD 2015). This knowledge gap is particularly evident in the aftermath of shocks and stresses, contexts where humanitarian and development actors take keen interest.

Here we provide novel insights into the temporal aspects of resilience in hazard affected contexts. In doing so we take advantage of two innovations. The first is a mobile phone panel survey to collect high frequency data after seasonal flooding in Eastern Myanmar. Mobile surveys have been used in a number of academic survey initiatives across Africa and Asia in recent years, capitalising on the rapid proliferation of cellular networks and mobile phone availability globally (Berman et al. 2017; Chesterman et al. 2017; Labrique et al. 2017). Phone surveys can be carried out in a number of formats, including via Short Message Services (SMS), Interactive Voice Recording (IVR) and computer-assisted telephone interviews (CATI) (Gibson et al. 2017). In the context of this study we focus on the latter: voice interviews conducted via a team of enumerators.

The advantages of mobile surveying are manifold. They allow respondents to be contacted remotely at a time of their convenience; provide timely and low-cost alternatives to traditional face-to-face survey administration; and permit results to be fed back to evaluators in near-real-time (Dabalen et al. 2016). They are particularly useful in post-disaster contexts, where access to field sites may be compromised due to political sensitivities, conflict or hazardous environments (Jones et al. 2018a).

The second innovation is the use of subjective modes of evaluation. In recent years, a range of subjective toolkits for resilience measurement have emerged (Marshall and Marshall 2007; Lockwood et al. 2015; Nguyen and James, 2013; Béné et al. 2016a; Jones and Samman 2016; Jones and D' Errico 2019). These offer a viable alternative to traditional objective methods which rely on external characterisations and evaluations of resilience (Jones, 2018). Rather than assuming that outside actors – typically NGOs or evaluation experts – are best placed to evaluate the resilience of others, subjective approaches take a contrasting epistemological stance. They seek to capture people's understanding of their own resilience and factor perceived capacities directly into the measurement process (Jones and Tanner 2017). Subjective methods are therefore concerned with measuring perceptions, judgements and preferences of the individuals being evaluated. They draw heavily on conceptual and methodological developments made in related fields like subjective wellbeing (Diener et al. 2000; Kahneman and Kruger 2006; Dolan et al. 2008), risk perception (Slovic 1987; Sjöberg 2000) and psychological resilience (Bonanno et al. 2007; Fletcher and Sarkar 2013).

An additional advantage of subjective methods for resilience measurement is the rapidity with which they can be administered (Claire et al. 2017). While objectively-evaluations of resilience can involve surveys made up of hundreds of separate questions (and up to two hours of survey administration), many subjective modules offer far quicker alternatives (see Jones 2018b). For example, subjective modules used by Marshall and Marshall (2007), Béné et al. (2016) and Jones and Samman (2016) can be administered with just a handful of questions and completed in less than five minutes. Indeed, it is the brevity of subjective evaluations that lends them to being administered via mobile surveys, with time limitations of 12-16 minutes before a high risk of termination (Dabalen et al. 2016; Gibson et al. 2017).

By combining the advantages of these two innovations, this paper provides novel insights into how resilience-capacities change in the aftermath of natural hazards. More specifically we are interested in three important questions. Firstly, we examine whether (and how) self-evaluated levels of resilience fluctuate on intra-annual timescales by comparing scores across our panel dataset. Secondly, we focus on the impacts of seasonal flooding, looking at whether directly affected households fare worse than those indirectly affected. Lastly, we see if there are differences in the length of time that floods impact on resilience scores across different socio-economic groups. Insights into these questions not only speak to the evidence needs of humanitarian and development actors, they shed valuable light on the validity of combining subjective methods with mobile phone surveys.

In tackling these three questions we use data collected in conjunction with the Building Resilience and Adaptation to Climate Extremes (BRACED) programme in the Hpa An township of Eastern Myanmar. As part of the programme, we carried out face-to-face household surveys with 1,072 residents in June 2017. Roughly one month after the baseline survey the area was hit by monsoon flooding. In order to investigate the effects of the flooding on the survey respondents, call centre enumerators carried out successive phone surveys every six-to-eight weeks for a period of twelve months. In total, eight separate waves of data collection were carried out allowing rapid evolutions in resilience and recovery to be quantified for the first time.

In this paper, we first provide background on the conceptual advancement of resilience, and its application in measurement approaches. We then detail data collection methods used for the survey, including descriptions of the subjectively-evaluated resilience module and steps taken in mobile surveying. Results are showcased, before we then discuss insights into the paper's main research questions. Lastly, we provide methodological challenges and routes forward for resilience measurement.

3.2. CONCEPTUALISING RESILIENCE AND HOW IT EVOLVES OVER TIME

Resilience means many things to many different people; a term heavily contested not only across academic disciplines, but within them (Brown 2014). Much of this confusion stems from the fact that resilience has been applied across a range of different fields, from engineering and ecology to its recent adoption within the social sciences (Olsson et al. 2015). More recently, resilience has come to prominence as a guiding framework for development and humanitarian actors (Brown, 2015). Indeed, resilience is now seen as an important international policy issue, with firm targets embedded into various United Nation's frameworks (UN 2015a; UN 2015b).

While the rise of resilience is an encouraging political development, its proliferation makes measurement particularly challenging. Unlike some health or poverty outcomes, resilience – at least as it relates to individuals or households – is neither directly observable nor measurable using a single indicator (Paloviita & Järvelä 2015). It also partially explains the dominance of qualitative analyses in our understanding of the resilience of socio-ecological systems to date (Adger, 2000; Walker et al. 2004; Folke, 2006; Cote and Nightingale, 2012). Indeed, some decry attempts at quantification as futile altogether (Levine, 2014).

Yet, this hasn't stopped a large number of quantitative assessment tools from emerging in recent years. The supply is in large part driven by calls for better ways of tracking the effectiveness of the large international investments flowing into resilience-building. One way of measuring resilience is to compare how people's wellbeing changes in response to a shock – usually measured through consumption, GDP or food security (Kimetrica, 2015; Arouri et al. 2015; Lazzaroni, et al. 2014). While informative, these approaches often make use of unrealistically narrow definitions of wellbeing (and resilience), and struggle to account for the influence of confounding factors (Schipper and Langston 2015; Bahadur and Pichon 2017). Moreover, they are severely limited in needing a shock to occur for someone's resilience to be compared.

As a result, most quantitative assessments take a different approach: evaluating resilience-capacities instead of outcomes. Resilience is commonly thought of as constituting a suite of related capacities (Kelman et al. 2016). For example, the Intergovernmental Panel on Climate Change's elaborate definition of resilience includes references to: 'coping', 'responding', 'reorganising', 'maintaining structure', 'adaptation', 'learning' and 'transformation' (IPCC 2014: 23). Capacity-based approaches concentrate on measuring these constituent capacities, often through use of objectively-evaluated proxy indicators (FAO et al. 2016; Smith et al. 2015; Sylvestre et al. 2012). Given that many of the capacities are themselves difficult to observe, indicators are often bunched together requiring considerable amounts of socio-economic data gathered from household surveys (Schipper and Langston 2015; FSIN 2014a).

One key advantage of capacity-based frameworks is that they encourage the recognition of resilience as a process (or set of processes) that continually evolve over time:

> "*[Social resilience] recognises uncertainty, change and crisis as normal, rather than exception. The world is conceived of as being in permanent flux. In consequence, social resilience is perceived as a dynamic process, rather than as a certain state or characteristic of a social entity.*" (Keck and Sakdapolrak 2013, pp 9)

Conceptualising it in this way recognises not only that resilience constitutes the capacity to respond to changing shocks and stresses, but that a household's resilience will itself persistently changing over time (Waller, 2001; Meadows et al. 2016). In other words, at any one moment in time, a household may exhibit comparatively low levels of resilience in responding to multi-hazard risk (say the plight of farming household following the death of an income generator), while there may be other times when the household's resilience-capacity is far higher (perhaps following harvest of a bumper crop).

Despite this, most resilience assessments are limited to single cross-sectional surveys (acting as a snap-shot in time). While well-resourced development programmes occasionally include mid-term and/or end-line surveys into their monitoring and evaluation (Yaron et al. 2018), panel surveys are sadly rare. One-off evaluations will therefore only measure resilience as it relates to the precise moment of data collection – failing to recognise that levels of resilience may have quickly shifted thereafter (Meadows et al. 2016).

The high financial and logistical costs of household surveys are largely to blame here, meaning that quantitative evidence of the temporal dimensions of resilience is limited – particularly on intra-annual timescales. Yet, there is good reason to believe that resilience may fluctuate on timescales shorter than a year. For example, the sustainable livelihoods literature has a long history documenting the influence of seasonality and intra-seasonal dynamics on livelihood outcomes and poverty – both of which contribute significantly to a household's resilience (Chambers et al. 1981; Longhurst et al. 1986; Deveroux et al. 2013). In recent years, some of this thinking has permeated the resilience literature. Though much of this relates to the adoption of adaptation and transformation as core components of the resilience of socio-ecological systems – concepts that are more commonly associated with multi-annual and decadal fluctuations (Kates et al. 2012). In what follows, we seek to fill a gap in quantitative evidence on the short-term dynamics of resilience by using high-frequency surveys administered before and after flooding in Myanmar.

3.3. STUDY APPROACH

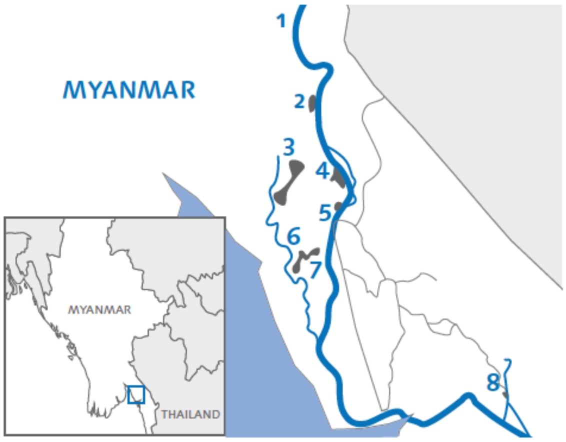
In order to track changes in resilience-capacities over time we use survey data collected from Hpa An township in Eastern Myanmar. Access to the site was facilitated through the BRACED Myanmar Alliance, a consortium of NGOs led by Plan International and consisting of five partner agencies: ActionAid, World Vision, BBC Media Action, the Myanmar Environment Institute and the UN Human Settlements Programme (UN-Habitat). The project was in operation between March 2015 to January 2018, delivering a range of resilience-related activities in eight townships across the country (see http://www.braced.org for further details).

The choice of Hpa An was taken on the basis of a number of factors (see Jones et al. 2018a). Principally, the site is prone to flooding during the monsoon season owing to its proximity to the Thanlwin river. Indeed, a month after the first set of baseline surveys, Hpa An was subjected to a series of heavy flood events that damaged communal infrastructure and livelihoods in the area. Unlike a number of other BRACED sites, Hpa-An is not affected by political instability. Lastly, the site in Hpa-An is made up of eight individual villages, each with different livelihoods, socioeconomic characteristics and risk profiles allowing for comparisons of resilience-capacities to be made.

3.2.1. Survey design and set-up

The first step in our survey design involved collecting baseline information through a traditional face-to-face household survey in June 2017. The exercise was carried out for all households across the eight villages served by the BRACED programme in Hpa An– essentially constituting a census of the area. After completing the surveys, each household was handed a mobile phone (a Singtech G9) and a small solar array. Handouts were done irrespective of whether respondents were previously in possession of a phone or not. Phone numbers of any other household members, as well as immediate neighbours, were collected to help ensure that respondents were easily contacted for the mobile surveys that followed.

Figure 11: List and location of the eight villages in the mobile panel survey



	VILLAGES INCLUDED IN THE RRR
1	Ta Kaung Boe
2	Wet Gyi
3	Kaw Yin (Upper)
4	Mote Ka Di
5	Hlar Kar
6	Pann Kone
7	Ya Thae Pyan
8	Kha Yae Kannar

Notes: Dark blue line represents the Thanlwin river (thick line) and its tributaries (thin lines). Grey shaded areas relate to village locations within Hpa An.

Immediately after the baseline survey a call centre was set up in the city of Yangon. Call centre enumerators comprised of individuals that took part in the initial survey and were trained in the use of computer-aided systems – involving automated dialling and the completion of online forms. Once set up, the call centre was used to remotely contact each of the households via the mobile phones distributed (or the alternative numbers collected).

A short oral survey was administered covering a range of resilience-related topics. The survey also gathered relevant socio-economic data. Given the risk of drop-out and survey fatigue (Debalen et al. 2015), mobile surveys were limited to 10-12 minutes in duration. In instances where respondents were unable to speak, an alternative time was arranged. Respondents were also given a small financial incentive to take part in the survey in the form of $0.50 airtime credit delivered to the phone after completion. Previous research has shown small incentives like these can help to ensure high response rates without biasing results (see Leo et al., 2015). Each individual wave took roughly six weeks in length, with seven phone waves completed across the study period. In total eighth survey rounds were completed: the initial face-to-face baseline followed by seven waves of mobile phone surveys.

Answers from the baseline were used to create a detailed profile of the socio-economic characteristics of each household. In some cases, households were unable to provide answers to all socio-economic questions. In addition, data on flood exposure started as of the first phone survey (which a small number of households dropping out of the panel in the intermediary period). Owing to the fact that a small number of households (5 in total) were solely affected by flooding in between Waves 1 and 2, and are likely to act as confounders, we remove these from the sample entirely.

Given that flood exposure is unlikely to be random, we weight our main analyses using an Inverse Propensity to Treat Weighting. Details of the IPTW process are described below, though require all households to be matched to a selection of socio-economic characteristics gathered during the baseline survey. We therefore exclude the small number of households that fail to answer all socio-economic questions in the initial survey. This limits the main sample to a partially balanced panel of 1072 households[12]. In addition, owing to the fact that drop-out rates in subsequent Waves of the survey appear non-random (and higher) amongst directly affected households, we also run the main analyses with a fully-balanced panel dataset comprised of 925 households. Result from the two datasets are compared later in Section 3.3, revealing similar trends against the main outcomes of interest.

Alongside the quantitative surveys, a series of semi-structured interviews were conducted using the mobile phone set-up. A total of 25 respondents were randomly selected from the survey population and asked a series of questions relating to resilience and coping strategies taken in response to flooding. Interviews lasted roughly 40 minutes in duration and were conducted using the same team of survey enumerators. Interviews were fully transcribed, providing insights to supplement findings from the quantitative survey. Given restrictions in the length of the interviews, respondents were asked only a handful of questions relating to factors associated with resilience. We augment as many of the quantitative results with qualitative insights, though recongise that this is far from uniform.

3.2.1 Measuring resilience using people's perceptions

Resilience can be measured in relation to a range of scales and systems. Here we clarify what we mean by resilience in the context of this study, *whose* resilience we refer to and resilience to *what*.

Our primarily interest is in examining social resilience – i.e. the ability of a social system to respond to external threats and changes while maintaining similar states of wellbeing or livelihood opportunity (Marshall and Marshall 2007; Adger et al. 2002). Core to this definition is the notion that social systems may need to re-organise in responding to evolving risk profiles: adapting and potentially transforming core functions as well institutional set-ups or power relations in order to sustain societal outcomes (Béné et al. 2014; Carr 2019). Viewed in this way, resilience can be seen as a process rather than a static outcome, and is typically characterised as made up of a range of inter-related capacities (FSIN 2014a).

[12] The original face-to-face baseline was conducted with 1203 households, meaning that the partially-balanced panel constitutes 89% of the original sample

In narrowing down our focus on social resilience, we are especially interested in a particular unit of analysis: the household (Alinovi et al. 2008). By doing so we recognise the importance of the household system as a crucial decision-making body in responding to external threats:

> *'As the decision-making unit, the household is where the most important decisions are made regarding how to manage uncertain events, both ex ante and ex post, including those affecting food security such as what income-generating activities to engage in, how to allocate food and non-food consumption among household members, and what strategies to implement to manage and cope with risks'.*
>
> (Alinovi et al, 2008:5).

Household resilience can be seen as sub-system of wider social resilience, and thus similarly concerned with the ability of individual household units to maintain levels of wellbeing and livelihood outcomes in the face of external threats. Indeed, household-systems have been the primary unit of focus for a number of resilience measurement studies (see D'Errico & Di Giuseppe 2018; d'Errico et al. 2018; Alinovi et al. 2010), allowing us to compare resilience outcomes from this study with a range of objectively-oriented evaluations.

While our focus on household units addresses the question of *whose* resilience, we must also clarify *to what?* One option is to treat resilience as hazard-specific. For example, a focus on flood resilience is concerned solely with the characteristics and indicators that reflect a household's ability to deal with flood risk. Yet, external threats rarely affect households in isolation. The impacts of flooding are likely to interact with, and be further compounded by, a whole host of wider socio-economic and environmental factors. Many of which may manifest through hybrid (or additional) threats further down the line – whether in the form of food price spikes or pest outbreaks.

Accordingly, resilience is increasingly framed in relation to multi-hazard risk. This recognises that the characteristics and indicators of resilience to different types of threats are often closely matched. In this study, we adopt this same multi-hazard framework, and seek to measure a household's capacity to respond to a broad range of socio-economic and environmental shocks (rather than a single specified threat). This approach is used in a range of household resilience measurement frameworks, including the Resilience Index Measurement and Analysis (RIMA) popularised by the United Nations Food and Agriculture Organisation (FAO) (Alinovi et al. 2008; Alinovi et al. 2010; D'Errico & Di Giuseppe 2018).

To measure household resilience, we use the Subjective self-Evaluated Resilience Survey (SERS) module (Jones and Samman 2016; Jones et al. 2018a; and Jones and D'Errico 2019). SERS capitalises on people's knowledge of their own resilience and asks people to self-evaluate themselves accordingly. Perception based tools like SERS have gained traction in recent years and are seen as a way of complementing traditional objectively-evaluated approaches to resilience measurement (Clare et al. 2017).

The SERS approach is based on a series of questions aggregated to form a single module (see Appendix B Table 18). Each question is comprised of a short statement linked to a specific resilience-related capacity. Statements are phrased in relation to a household's ability to deal with hypothetical future threats. Respondents are asked to rate their levels of agreement with the statements using a 5-point Likert scale (see Appendix B Table 18). Answers to each question are numerically converted, with scores calculated using an equal weighted mean for all capacity questions. Scores are then normalised, resulting in a single resilience score ranging from 0 (lowest resilience) to 1 (highest resilience).

SERS is designed to be flexible. The choice and number of statements can be changed in order to mimic a range of resilience frameworks. In the context of this study, we define resilience in accordance with the '3As' model first introduced by Bahadur et al. 2015 – referred to herein as the SERS-3A model, or simply SERS. Under the 3A model, resilience is viewed as consisting of three core capacities: anticipatory capacity (the ability to anticipate threats and respond ahead of time); absorptive capacity (the ability to bounce back after a threat) and adaptive capacity (the ability to change core societal structures and functions in response to changing risk profiles). This model of resilience has been used widely by a range of development actors and forms the conceptual basis of the $130M BRACED programme. While the majority of our analysis makes use of the 3As, we also compare results to other popular resilience frameworks, including those that feature transformative capacity (Béné et al. 2014).[13]

When evaluating SERS, it is important to clarify what the measure actually represents. Specifically, SERS is meant as a momentary marker of a household's resilience to deal with future threats (expressed as multi-hazard risk rather a singular hazard). Self-evaluations aim to be forward-looking, gauging the extent to which households can deal with forth-coming hypothetical threats at a given moment in time. While the SERS model inherently cannot cover all aspects of resilience, and other capacities undoubtedly remain, it gives a useful indication of the household's resilience and is comparable with similar objectively-oriented resilience measures.

[13] We return to examine differences amongst SERS variants in the Robustness checks section and Section 3.4

Table 5: List of resilience-related capacity questions used in the 3A variant of the Subjectively-Evaluated Resilience Score

Preamble: 'I am going to read out a series of statements. Please tell me the extent to which you agree or disagree with them.' [Read out each statement and ask] 'Would you say that you strongly agree, agree, disagree, strongly disagree or neither agree nor disagree that:'

Resilience-related capacity	Survey question
Absorptive capacity	Your household can bounce back from any challenge that life throws at it
Adaptive capacity	If threats to your household became more frequent and intense, you would still find a way to get by
Anticipatory capacity	Your household is fully prepared for any future disasters that may occur in your area

Notes: For a full list of the original capacity questions, as well as other SERS variants see Appendix B Table 1 and Jones and D'Errico (2019).

In the context of this paper we are primarily interested in how hazards impact on resilience scores over short periods of time. We note that there are many factors that can affect a household's resilience. Indeed, changes in resilience are likely to occur whenever there are factors that influence the status of resilience-related capacities – many of which are likely to take place in the absence of a hazard. However, the occurrence of a shock (in this case heavy seasonal flooding) can be expected to have an immediate and consequential impact on household's resilience capacities (Linnenluecke 2012) - akin to a natural experiment. This allows us to easily infer how exposure to one hazard influences resilience levels going forward, isolating the temporal nature of this impact using our unique high-frequency panel. It is for this reason that we focus on the impacts of the June flooding in Hpa An in this study. Yet, we note that the same methodology could easily be applied to tracking slower onset changes to resilience capacities in other contexts.

3.3. RESULTS

Below we present findings from across the various waves of surveying in Hpa An (for clarity, we refer to the initial face-to-face survey as the baseline, and the subsequent seven rounds of mobile phone surveys as waves 1-7). We begin by describing socio-economic and environmental risk conditions of our study site, followed by insights into the three research questions addressed in this paper.

The left-hand column of Table 6 presents unweighted summary statistics of socioeconomic characteristics of households (we return to describe the nature of the weighted sample in the right-hand columns later). The sample is characterised by low socio-economic wellbeing and high levels of disaster risk (further visual breakdowns are presented in Appendix B Figure 22). Around 30% of respondents have not completed any form of formal education, this compares with the national average of 16% for those aged 25 and over (GoM 2017a).

Agriculture is the primary source of livelihood with casual labour and remittances playing an important role. Close to one in five head-of-households classifies themselves as a widower – with the national average being 10.4% for women and 3.1% for men (GoM 2017b). Moreover, the mean Progress Out of Poverty (POP) score[14] for households in the survey is 41 – roughly equivalent to a 16% likelihood of being below the 2010 national poverty line (see Schreiner 2012). While this indicates that poverty is present, it is not prevalent, and is similar to Myanmar's average of 19.4% of households below the national poverty line in 2015 (World Bank 2017).

[14] The Progress out of Poverty Score was created by the Grameen Foundation, it uses 10 simple questions, such as "What material is your roof made out of?" or "How many of your children are in school?" to determine the likelihood that a particular household is living below a given poverty line. The likelihood is derived from the value of the score, which ranges between 0 (extremely poor) to 100 (not poor). Thus, the lower the score the higher the likelihood for a household to be poor. For more see Schreiner (2012).

Table 6: Summary statistics for the Hpa An panel survey (unweighted and weighted)

Variable	Unweighted sample				Weighted sample			
	Overall (n = 1072)	No hazard (n = 994)	Floods (n = 78)	*p*	Overall (n = 1072)	No hazard (n = 994)	Floods (n = 78)	*p*
Baseline resilience score	0.54 (0.18)	0.54 (0.18)	0.56 (0.13)	*0.17*	0.5 (0.0)	0.5 (0.0)	0.6 (0.0)	*0.65*
Dummy for education of household head				*0.33*				*0.78*
None	312 (29.1)	285 (28.7)	27 (34.6)		312 (30.0)	285 (29.1)	27 (30.9)	
Some schooling	760 (70.9)	709 (71.3)	51 (65.4)		760 (70.0)	709 (70.9)	51 (69.1)	
Age of respondent	47.2 (13.0)	47.2 (12.9)	47.0 (13.5)	*0.86*	46.8 (1.1)	47.2 (0.4)	46.4 (2.3)	*0.74*
POP poverty score (high score = higher likelihood of not in poverty)	41.7 (13.3)	42.1 (13.5)	37.4 (9.6)	*< 0.001*	40.6 (0.5)	41.7 (0.4)	39.4 (1.0)	*0.03*
Mean number of HH occupants	4.66 (2.03)	4.66 (2.04)	4.58 (1.97)	*0.71*	4.8 (0.2)	4.7 (0.1)	4.8 (0.3)	*0.56*
Dummy for farmer as primary income source				*0.006*				*0.60*
Farmer	506 (47.2)	457 (46.0)	49 (62.8)		506 (45.5)	457 (47.2)	49 (43.8)	
Non-farmer	566 (52.8)	537 (54.0)	29 (37.2)		566 (54.5)	537 (52.8)	29 (56.2)	
Dummy for remittance as primary income source				*0.73*				*0.99*
Non-remittance	727 (67.8)	676 (68.0)	51 (65.4)		727 (67.9)	676 (67.8)	51 (67.9)	
Remittance	345 (32.2)	318 (32.0)	27 (34.6)		345 (32.1)	318 (32.2)	27 (32.1)	
Gender of HH head				*0.25*				*0.83*
Male	830 (77.4)	765 (77.0)	65 (83.3)		830 (78.1)	765 (77.4)	65 (78.8)	
Female	242 (22.6)	229 (23.0)	13 (16.7)		242 (21.9)	229 (22.6)	13 (21.2)	
Respondent gender				*0.72*				*0.87*
Male	563 (52.5)	520 (52.3)	43 (55.1)		563 (52.0)	520 (52.5)	43 (51.4)	
Female	509 (47.5)	474 (47.7)	35 (44.9)		509 (48.0)	474 (47.5)	35 (48.6)	

Notes: For continuous variables means are presented with standard deviations in parentheses, an unequal variance t-test is used to compare means; for categorical variables frequencies are presented with percentages in parentheses, a Pearson's chi-square test is used to examine differences in distributions across groups. Statistics are provided only for households that complete all eight waves of the panel survey (reducing the sample from 1203 to 985).

During the baseline interview, respondents were also asked a number of questions related to risk perception. Appendix B Figure 23 shows that, while the area is occasionally affected by drought and cyclones, floods are by far the most frequently occurring climate hazard.

To get a better sense of levels of resilience in pre-monsoon conditions, we also look at associations between subjectively-evaluated resilience and various socio-economic traits by running a series of multivariate regressions (see Appendix B Section 1). Using this single cross-section of the survey, we observe that baseline resilience scores are associated with a number of socio-economic traits. Higher education of the household head, higher POP poverty scores (i.e. lower likelihood of being in poverty), female headed-households, greater life satisfaction, higher numbers of household occupants and reliance on remittance as a primary source of income are all positively associated with subjectively-evaluated resilience. Conversely, high dependence on farming as well as distance from the Thanlwin river are negatively associated with resilience. Reassuringly, many of these socio-economic characteristics appear to align with quantitative and qualitative understandings of the drivers of household resilience within the resilience literature (D'Errico and Di Giuseppe 2018). The age and gender of respondents also exhibit statistically significant relationships with SERS scores.

3.3.1. Changes in resilience over time

While the baseline results are of some interest, the real value from the Hpa An dataset is found in the full panel dataset. As outlined above, a few weeks after the baseline survey was conducted a series of flood events struck the area between June-July 2017. Direct observations of flood exposure for the area are lacking. However, we present simulated discharge of the Thanlwin for Hpa An town (adjacent to the 8 surveyed villages) using ensemble forecasts from the Global Flood Awareness System (GloFAS) for the period of the survey in Figure 12a (Alfieri et al. 2013). We also overlay dates of the various survey waves shown as vertical lines. As respondents were contacted on different days during each wave of the mobile survey, lines represent the average length of time from the baseline (the solid vertical line) for all households in subsequent waves (dashed lines).

A sharp uptick in river discharge occurs just after the baseline survey, with levels decreasing gradually thereafter. Large seasonal fluctuations like this are not uncommon in Hpa An. Indeed, insights from the baseline survey show that one in five households report being hit by floods at least once a year (20.8%) – see Appendix B Figure 23. Another 42.1% are affected by floods every couple of years. Accordingly, while Figure 23c shows that monsoonal river discharge in 2017 was not especially exceptional, various accounts from the semi-structured interviews point to the extent of localised impacts:

> '*The roof of our house was damaged. As the roof of our house is made with leaves, it was blown away by wind. We had to sleep on the floor under our house because the whole house was wet. We fixed the house by buying leaves for the roof of the house. We didn't get any help from others. We fixed it with money of our own. The water level rose up to our knee from the ground.*' (ID#1, Female, Seamstress)

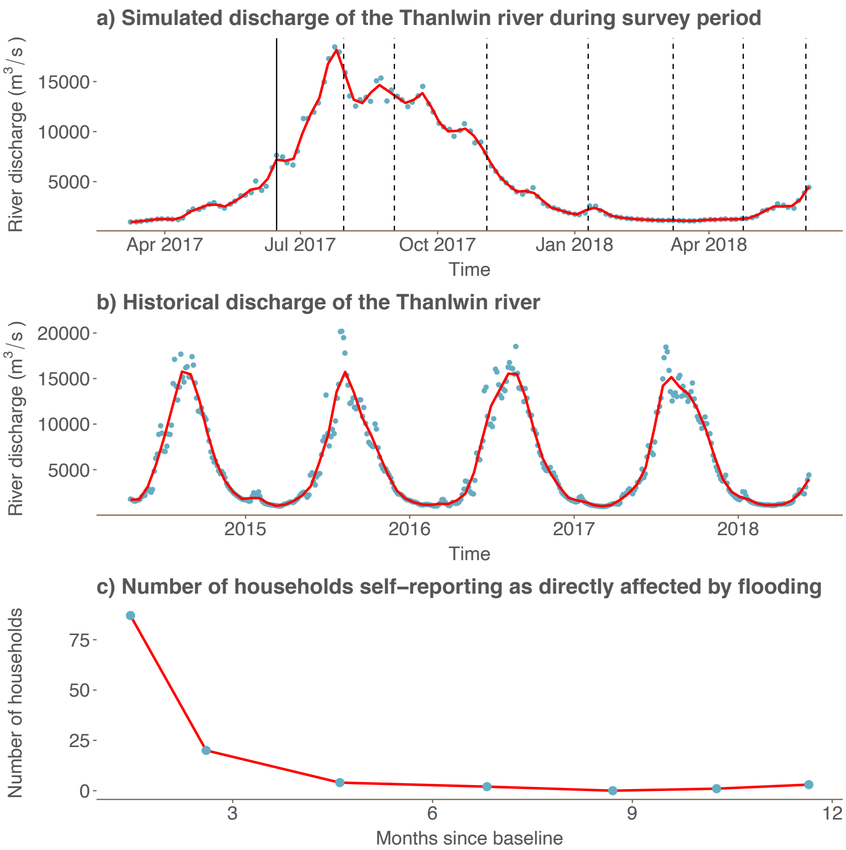
Note that the above quote also illustrates the importance of framing resilience in relation to multi-hazard risk. Even though the principle threat came from water inundation, high wind speeds also played a damaging role in the Hpa An floods. Interviewees report numerous other instances of damage to household property and negative implications for livelihoods, with similar impacts on communal infrastructure and local markets.

Figure 12c) reports the extent of flood exposure amongst surveyed households. At the start of each round of surveying, households were asked whether they had been impacted by a flood event since the last point of contact – defined as one inflicting a large negative effect on the household's way of life[15]. As Figure 12c shows, a number of households

[15] See Appendix B Table 20 for survey question wording

reported as directly impacted by flooding between the baseline and Waves 1 (n=87) and 2 (n=19) of the survey, coinciding with peak discharge of the Thanlwin river[16].

Figure 12: Thanlwin River discharge and frequency of self-reported flooding during the course of the Hpa An survey



Notes: Vertical dashed lines in Panel a) represent different waves of the mobile phone panel survey. Households classified as directly affected in Panel c) are those that self-report as having experienced a flood event with serious negative impacts the household's way of life in the previous month (baseline) or since the last wave of the survey (for mobile phone waves).

Given the extent of flooding and localised impacts, we might expect to see this reflected in changes in levels of resilience-capacities amongst households in Hpa An. To investigate this further we plot mean SERS scores across the entire panel for the full Hpa An sample in Figure 13a. We also show the distribution and density of subjectively-evaluated resilience scores for each of the survey waves in Appendix B Figure 25.

Owing to the fact that two different methods of survey administration were used (face-to-face during the baseline and mobile for all remaining panel waves) we mark the period between the baseline and first wave of the mobile survey with a dotted line. Indeed, insights from related academic fields reveal well documented differences between these two modes of administration. For example, Dolan and Kavestos (2017) note that

16 Note that these numbers are limited to n=78 (W1) and n=5 (W2) in the partially balanced dataset – owing to the exclusion criteria outlined in 3.3.1

subjective wellbeing scores are significantly higher for phone surveys than for face-to-face interviews (2016).

Coincidently, the gap between the face-to-face and phones surveys is greatest when the majority of flood events are reported to have taken place in Hpa An. Thus, while it may be surprising to see a large jump in resilience scores between the baseline and Wave 1 of the survey, a large part of this is likely due to mode effects[17]. The fact that scores immediately drop after Wave 1 is also supportive of this interpretation. However, we choose to retain data from the baseline survey as it contains useful information on pre-flood conditions. In doing so we operate on the assumption that any differences between the two modes are systematic and consistent across socio-economic groups. We note that results should be carefully interpreted with this caveat in mind.

As is clear, despite the rise in mean resilience scores between the baseline and first wave, there appears to be a dramatic and consistent reduction between Waves 1 and 4 (roughly 1-7 months after the baseline). Scores then rebound sharply during Wave 5 before appearing to level off somewhat for the final wave of the survey just over 10 months since the baseline survey.

[17] A similar jump in scores between face-to-face and mobile phone modes is registered in a parallel BRACED survey run in the adjacent town of Mudon, providing further confidence in the existence of positive mode effects.

Figure 13: Change in subjectively-evaluated resilience scores over time

Notes: Shaded red areas in Panels a-c) represent periods of active flooding. Dotted lines in panels a-c represent the difference between face-to-face and mobile phone phases of the panel survey. Horizontal coloured lines are baseline resilience scores. The shaded blue area in Panel d) shows a stylised representation of the area used to calculate the Area Under the Curve (AUC).

We can also look at differences in resilience scores based on self-reported flood exposure. Figure 13b differentiates between households directly and indirectly affected by flooding between the baseline and first two waves of the phone survey. Here it is important to note that given the survey is a census of eight villages on the banks of the Thanlwin, we assume that flooding during this period had some degree of impact on all households. This could relate to access to: the status of communal assets; effects on local markets and livelihood opportunities; or demands of support from immediate family and neighbours. This assumption is supported by qualitative insights from the key informant interviews that report a wide range of localised impacts across all households in the area. As such, we classify all remaining households as 'indirectly' affected by the flood events, rather than 'unaffected'.

Directly affected households have lower resilience scores immediately after the main flood period. This is despite resilience levels being slightly higher for this group prior to flooding. Scores do appear to converge towards the fourth wave of mobile surveying and rebound similarly towards the end of the survey (though with slightly lower scores than indirectly affected households). It is also possible to account for different starting values prior to flooding by normalising baseline resilience scores. Figure 13c reveals starker differences between directly and indirectly affected households with similar patterns of convergence (and divergence) towards the end of the panel.

3.3.2. Examining the impact of natural hazards on resilience over time

It is clear from Figure 13 that levels of resilience drop sharply for all households after flooding. However, a host of wider shocks, seasonal factors and psychological traits could also be affecting changes in self-reported scores. To get a better sense of the specific role that floods played in influencing resilience scores over time, we employ a series of difference-in-differences regression specifications. Given the issue of spillover in flood impacts and coping strategies as highlighted earlier, we do not see these exercises as formal impact evaluations. Neither are they an attempt to formally quantify the magnitude of flood impacts on resilience. Rather, we use them to address a more basic question of whether differences in exposure to natural hazards affect self-reported resilience scores over time. We see this as a key test of the validity of the SERS module.

Our first method uses a generalised difference-in-differences approach with multiple time periods (Angrist & Pischke, 2008; Bertrand 2004). Here $Resilience_{ht}$ corresponds to the SERS resilience score for household *h* during time period (wave) *t*.

$$Resilience_{ht} = \beta_1 post_t + \beta_2 f_h + \beta_3 (post_t \cdot f_h) + \psi_h + \emptyset_t + e_{ht} \qquad 1)$$

$post_t$ is an indicator of period, with 0 given for the pre-flood baseline and 1 for all post-flood waves. f_h denotes the severity of the flood's impact on the household (0 for households that are indirectly affected by the flooding and 1 for those directly affected). $\psi_h$is an individual fixed effect (corresponding to each household in the survey), and $\emptyset_t$ is a time fixed effect (with separate dummies for each individual wave of the survey).

The $post_t \cdot f_h$ interaction estimates the change in pre- and post- resilience scores between those directly and indirectly affected by flooding, with the main entity of interest given by the coefficient β_3. To account for the fact that flood exposure is likely to have varied across the eight surveyed villages, we cluster-standard errors at the village level (though repeat the analysis with errors clustered at the individual level as a robustness check). Given the small number of village-level clusters (n=8), standard errors are estimate using a Wild clustered bootstrap (Cameron, Gelbach and Miller 2008)[18].

A key assumption in difference-in-differences models is parallel trends between comparison groups (Angrist & Pischke 2008). While we do not have much data on household outcomes prior to flooding, it is reassuring to see that household characteristics between directly and indirectly affected households (shown in the unweighted sample in Table 6) appear to be relatively homogenous during the baseline. To further account for the risk that imbalances in composition may be affecting trends over time, we also combine the difference-in-differences model in Equation 1 with a weighting procedure (Stuart et al. 2014). Specifically, we use an Inverse Propensity to Treat Weighting (IPTW).

---

[18] We also see no differences in main outcomes of interest when using traditional cluster-robust or bootstrapped standard errors as an alternative

The first step involves running a logistic regression to determine the probability of being directly affected by the floods, *p*. A probability is obtained by regressing f_h against a range of socio-economic baseline variables (those listed in Table 6). A weight is then given to each household, using an inverse probability of treatment (Imbens 2000), with households that are directly affected assigned $\frac{1}{p}$, and those indirectly affected given $\frac{1}{1-p}$. These weights are then used in calculating Equation 1.

Table 7: Difference-in-differences between direct and indirectly affected households across all waves of the survey

	Resilience-over-time (DID) (Unweighted)	*Resilience-over-time (DID)* (Weighted using IPTW)
f · post (Difference in Differences)	-0.08*** (0.02)	-0.06*** (0.02)
f (1=Directly affected by flooding)	-0.13*** (0.02)	-0.14*** (0.02)
post (1=Periods after flooding)	-0.01 (0.01)	0.004 (0.01)
Household fixed effects	YES	YES
Wave fixed effects	YES	YES
Observations	8,765	8,765
Adjusted R-Squared	0.29	0.21
Residual Std. Error	0.707 (df = 8740)	0.981 (df = 8740)

Note: Values indicate Beta coefficients with Standard Errors clustered at the village-level using a wild cluster bootstrap (with 200 replications) and shown in parentheses, *p<0.1** p<0.05p***p<0.01

Table 7 reports the estimates for the two models. In both cases, the coefficient for differences in resilience scores between the two groups (f · post) is negative and significant. While the effects are somewhat reduced for the weighted sample, results from both specifications suggest that households directly impacted by the floods have lower resilience scores over time than those that are indirectly affected (8% lower for the unweighted sample, and 6% lower for the IPTW sample).

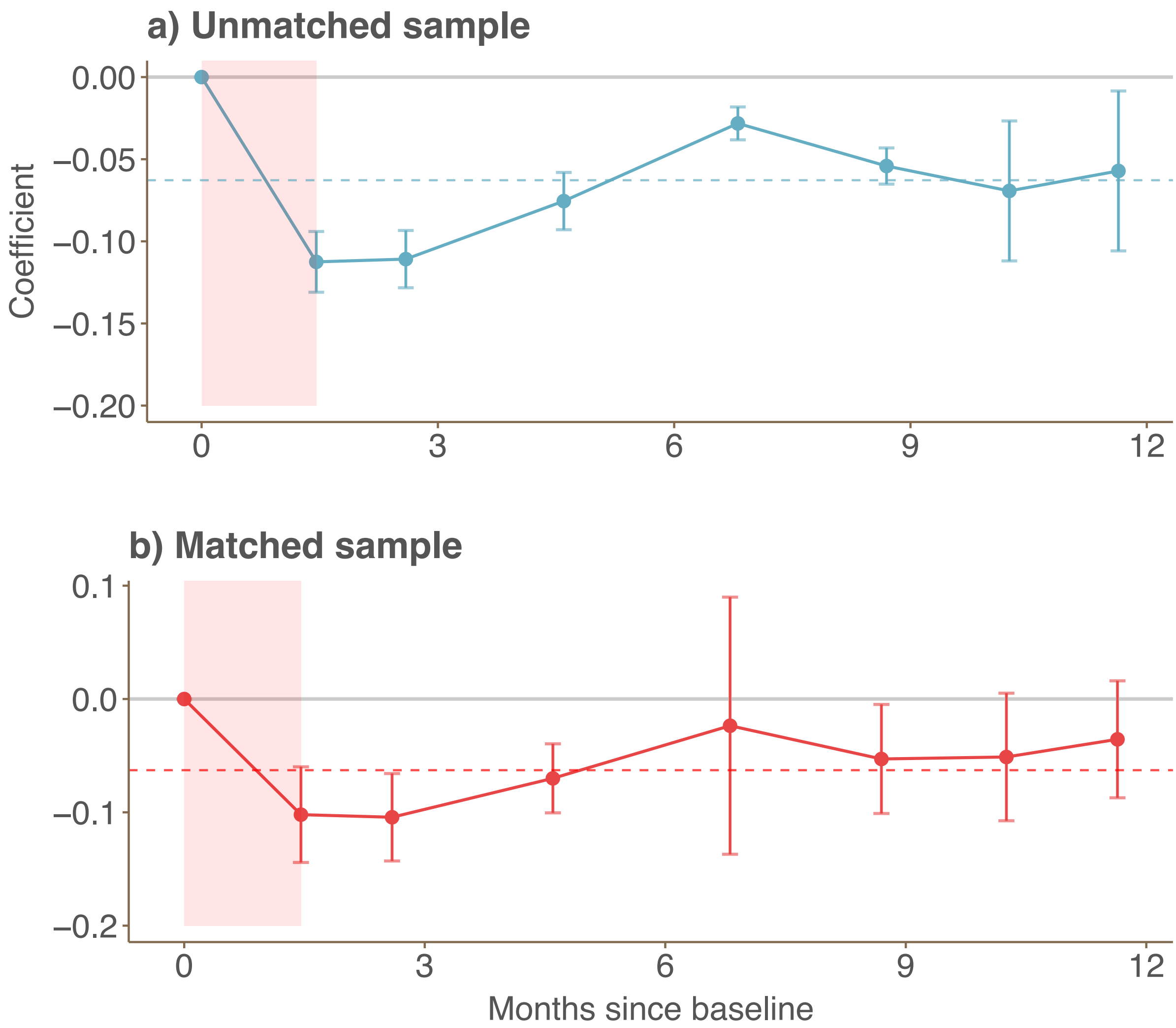
So far, we have focused the analysis on comparisons between the pre-flood baseline and all post-flood periods at once. However, we are also keen to have a more detailed look at how resilience scores vary over time, gaining insights into length of impact. To do so we modify Equation 1 to run an event study specification with interactions between the flood impact variable, f_{hv} and time dummies for all waves during the survey.

$$Resilience_{ht} = \sum_{k=0}^{7} \beta_k \mathbf{1}\ (t_h = t^* + k\ ) \cdot f_t + \psi_h + e_{ht}$$

2)

Here f_t is an indicator of whether the household experienced a flood during the survey period. $\mathbf{1}\ (t_h = t^* + k\ )$ indicates the number of waves relative to the baseline t^*, with *k* ranging from 0 (i.e. baseline) through to Wave 7 of the phone survey (*k* = 7).

Figure 14: Differences in self-evaluated resilience scores for households directly and indirectly affected by flooding over time



Notes: Graph shows outputs from the event study specification. Dots represent beta coefficients, with whiskers as 95% confidence intervals. The red shaded area represents the period of time when extensive seasonal flooding affected the Hpa An area. The dashed horizontal lines represents the average of all coefficients for survey waves after the period of flooding (waves 1-7). Standard errors are clustered at the village level using a Wild clustered bootstrap (200 replications). Coefficients are in relation to the number of months since the initial face-to-face baseline survey.

Figure 14a shows a sharp drop in resilience scores for directly affected households in the first months following the baseline. Scores do appear to rebound somewhat, though convergence is somewhat inconsistent. The negative value of coefficients for all lead waves suggests that the impacts of flooding on directly affected households persist for some time. Outcomes from the weighted sample (Figure 14b) also reveal how directly affected households fare worse compared with those indirectly affected – closely matching those in the unweighted sample. Noticeably, scores for both approaches rebound somewhat towards the end of the panel survey – though this is inconsistent in nature, with a slight jump in Wave 4 (large standard errors present in the IPTW sample).

3.3.3. Calculating recovery rates using a resilience-over-time score

The generalised DID and event study estimates tell an interesting story of how flood exposure affects household's perceptions of resilience over time. Yet, the approach does not make use of all information across survey waves. For example, each post-flood score is weighted evenly, even though there are differences between the time taken to collect each wave (see Figure 12 for average dates of wave completion). It is also difficult to compare and dissect associations with a range of time invariant factors – such as wealth and education. To shed further light on how flooding affects resilience over time we examine our survey data using a second method: an Area Under the Curve (AUC) approach.

AUC approaches are commonly used in comparing temporal changes in aggregate outcomes, such as subjective wellbeing (Kimball et al. 2015), stress-level monitoring (Eckhardt 2001) as well as various other health-related outcomes (Mohiyeddini el atl. 2015; Pruessner er al. 2003). More recently, they have been used to analyse resilience and recovery rates for hard infrastructure and ecological systems in the aftermath of disasters (Todman et al. 2016; Zobel 2014). Here, we borrow from these approaches and extend their application to examine social systems through tracking household-level outcomes.

Specifically, we calculate the total AUC for resilience scores of each individual across all waves of the panel. As shown in the stylised example in Figure 13d, this constitutes the shaded area under the resilience curve. Here, the AUC, $Resilienceovertime_{ht}$, can be expressed as the integral of the resilience curve $Resilience_h(t)$ between baseline (*t*=0) and the remaining seven waves of the mobile phone survey.

$$Resilienceovertime_{ht} = \int_{t=0}^{7} Resilience_h(t)dt \qquad 3)$$

In essence, we take $Resilienceovertime_{ht}$ (herein referred to as a 'resilience-over-time') to represent cumulative levels of resilience for households over the course of the survey: a proxy for recovery rates. As scores are unique to each household, they can be used to compare recovery levels across socio-economic groups.

For simplicity and ease of interpretation, intervals between each wave are assumed to be linear (and any missing values interpolated relative to the nearest scores on either side). Households with more than three missing values across the various waves, as well as those lacking in resilience scores for the baseline and endline surveys are removed entirely from the sample.

A key advantage of the AUC analysis is that it weights resilience scores according to the length of time taken for each wave to be completed since the last. In theory, households that are heavily impacted by the flood events will exhibit sharper and most sustained drops in average resilience scores in the months that precede reporting. This would in turn be reflected in lower resilience-over-time scores compared with households indirectly affected by flooding.

To formally examine the impact of the floods, and factors commonly associated with resilience-over-time scores, we run a series of OLS regressions. In Equation 4 we present a basic model set-up with the dependent variable $Resilienceovertime_{hv}$ as the AUC for the period up to 12 months after the baseline. This mimics a similar set up used by Kimball et al. (2015) in tracking the impacts of life events on levels of subjective wellbeing over time.

Here, the impact is a dummy variable, f_{hv}, for households that self-report as directly impacted by flooding between the baseline and the first two months of the survey. Controls for socio-economic variables, s_{hv}, and factors commonly associated with resilience, including risk perception, p_{hv} are added. Importantly, each household's resilience score during the baseline, $Resilienceovertime_{hv,-1}$ is added to account for baseline imbalances in mean scores as recommended by Manca et al. (2005). Lastly, ξ_v represents a village-level fixed-effect with the error term captured by e_{hv}.

$$Resilienceovertime_{hv} = \beta_1 Resilienceovertime_{hv,-1} + \beta_2 f_{hv} + \beta_3 s_{hv} + \beta_4 p_{hv} + \xi_v + e_{hv}$$

4)

To account for potential differences in the makeup of directly and indirectly affected households, we repeat the exercise using an inverse probability of treatment weighting (IPTW), as per the DiDs above.

Results of the regression models are shown in Table 8. Differences in resilience-over-time scores between those directly and indirectly-affected households are statistically significant and consistent across all models, with directly affected households exhibiting lower overall scores than those indirectly affected.

In terms of associations with wider socio-economic variables, age of the household head has a strong positive association with resilience-over-time scores for both unweighted and weighted samples. Reasons for this are likely to do with a lack of economic opportunities available to younger individuals – particularly in relation to work outside of Hpa An – as well as more established social networks and capital. This is well reflected in the qualitative interviews, with one interviewee observing that '*households where members are not old enough to stay and work in Thailand are in unstable conditions in the village, they struggle to earn for their family*' (ID#18, Female, Farmer). The number of household occupants is also strongly associated with resilience, with great occupancy associated with higher resilience-over-time.

Households that derive a primary livelihood from farming are linked with higher resilience-over-time (though the effect is inconsistent for the IPTW). Numerous interview responses also reflect this trait, noting how '*people without a farm are unstable, they have difficulty in living*' (ID#3, Male, Farmer). Interestingly, while the household's poverty index (measured through the POP poverty score) exhibits a positive relationship with resilience-over-time scores for most models, the strength of associations with education of the household head is far less pronounced (though positive effects are seen across all models).

When it comes to risk factors, higher perceived flood sensitivity and flood exposure are negatively linked with resilience (though only the former is statistically significant). Life satisfaction is positively associated with resilience-over-time, while distance to the nearest road is negative and statistically significant – likely reflecting wider socio-economic circumstances such as access to markets and ease of movement. Female-headed households have significantly lower resilience-over-time scores compared to male-headed households. Lastly, it is curious to note that income diversity is negatively associated with resilience (households with more sources of income are linked to lower resilience-over-time scores).

Table 8: Factors associated with resilience-over-time for the entire Hpa An sample

	AUC for unweighted sample			AUC for IPTW sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Dummy for flood impact (0=Indirect; 1=Direct)	-8.26** (4.18)	-7.87** (3.25)	-9.98*** (2.55)	-11.44** (4.64)	-12.03*** (4.47)	-10.06*** (3.80)
Dummy for education of household head (0=None; 1=Some schooling)		0.29 (1.32)	2.31 (1.88)		3.00 (3.13)	4.96* (2.66)
Age of respondent		0.24*** (0.03)	0.27*** (0.04)		0.18*** (0.05)	0.28*** (0.04)
POP poverty score (high score = higher likelihood of not in poverty)		0.13*** (0.05)	0.13** (0.06)		0.14** (0.06)	0.08 (0.06)
Mean number of HH occupants		1.07*** (0.26)	1.19*** (0.46)		1.69*** (0.62)	1.68** (0.68)
Dummy for farmer as primary source of income (1=Farmer)		4.66*** (1.05)	7.19*** (1.37)		2.63 (1.96)	3.23* (1.84)
Dummy for remittance as primary source of income (1=Remittance)		-1.13 (1.68)	-1.93 (2.21)		4.00* (2.11)	3.19 (2.02)
Gender of HH head (1=Female)		-4.30*** (1.10)	-4.92** (2.00)		-7.09** (2.84)	-7.86** (3.39)
Respondent gender (1=Female)		-1.71 (1.40)	-1.18 (1.22)		-1.18 (1.44)	0.88 (1.90)
Risk perception: dummy for flood sensitivity (0= Not at all a problem; 1=Very serious problem)			-6.85*** (1.67)			-6.19** (3.10)
Risk perception: dummy for flood exposure (0 = Fewer than once a year; 1=Once a year or more)			-1.86 (1.22)			-2.04 (2.26)
Life satisfaction (higher score = higher life satisfaction)			3.74*** (1.26)			5.05*** (1.49)
Dummy for more than one source of livelihood (1=More than one)			-6.29*** (1.61)			-7.12*** (2.26)
Distance to the river (log+1)			0.19 (1.18)			0.38 (1.06)
Distance to nearest road (log+1)			-7.16*** (1.14)			-8.34*** (1.83)
Observations	1,072	1,072	1,052	1,072	1,072	1,052
Adjusted R2	0.21	0.23	0.20	0.26	0.28	0.31
Residual Std. Error	28.75 (df = 1062)	28.51 (df = 1054)	29.09 (df = 1035)	39.17 (df = 1062)	38.54 (df = 1054)	37.90 (df = 1028)

Note: The outcome variable in all models consists of the resilience-over-time score (i.e. the area under the curve for the SERS-3A module over the course of the 8 rounds of surveying) weighted using IPTW. All models include controls for baseline resilience scores and Village fixed effects. Models 1-3 consist of the full Hpa An sample, while Models 4-6 are restricted to households directly affected by flooding between the baseline and Wave 1 of the survey. Values indicate Beta coefficients with Standard Errors clustered at the village-level using a wild cluster bootstrap with (200 replications) shown in parentheses, *p<0.1** p<0.05p***p<0.01

3.3.4. Examining the impact of natural hazards on different socio-economic groups

The analysis above helps us in understanding the associations between resilience-over-time and a variety of socio-economic traits for all households in the Hpa An sample. While these are informative, we are especially interested in knowing whether exposure to the floods affected socio-economic groups in different ways. In other words, did particular social groups fare better or worse when directly exposed to flooding (compared to those indirectly affected)?

To explore this in more detail we augment Equation 4 by adding interactions between flood exposure (f_{hv}) and covariates for both socio-economic status (s_{hv}) and risk perception (p_{hv}) as shown below.

$$Resilienceovertime_{hv} = \beta_1 Resilienceovertime_{hv,-1} + \beta_2 f_{hv} + \beta_3 s_{hv} + \beta_4 p_{hv} + \beta_5 (f_{hv} \cdot s_{hv}) + \beta_6 (f_{hv} \cdot p_{hv}) + \xi_v + e_{hv}$$

5)

We carry out the analysis with the partially balanced sample. However, we recognise that drop-out rates for directly affected households are higher and are unlikely to be non-random. We therefore also run the analysis with a fully balanced dataset – noting that this further reduces the sample group of directly affected households (n=46 as opposed to than n=78 in the partial sample).

Table 9 presents results from the interacted variables in both samples. Although the group size of directly affected households is relatively small in both cases, a number of variables are seen as significantly associated with resilience-over-time scores when interacted with the flood exposure (f_{hv}).

Table 9: Associations with resilience-over-time scores with interactions between flood exposure and a range of socio-economic and risk factors

	Partially balanced sample		Fully balanced sample	
	Unweighted	IPTW	Unweighted	IPTW
	(1)	(2)	(3)	(4)
Dummy for household head education (0=None; 1=Some schooling) * Flood exposure (0= Indirect; 1=Direct)	0.55 (4.03)	5.49 (5.40)	8.63 (7.60)	7.30 (12.60)
Age of respondent * Exposure to flooding	0.04 (0.24)	0.07 (0.23)	0.35 (0.48)	0.42 (0.51)
POP poverty score (high score = higher likelihood of not in poverty) * Exposure to flooding	-0.05 (0.34)	0.002 (0.34)	0.49 (0.39)	0.58 (0.39)
Mean number of HH occupants * Exposure to flooding	1.15 (2.61)	2.29 (2.36)	2.97 (2.72)	2.34 (1.72)
Dummy for farmer as primary source of income (1=Farmer) * Exposure to flooding	-8.99 (8.63)	-13.64* (7.45)	-1.59 (6.19)	-9.25 (7.16)
Dummy for remittance as primary source of income (1=Remittance) * Exposure to flooding	5.37** (2.26)	10.06*** (2.77)	1.95 (4.94)	13.26* (7.18)
Gender of HH head (1=Female) * Exposure to flooding	-15.59** (6.13)	-11.45* (6.07)	-28.73*** (9.19)	-31.48*** (5.88)
Respondent gender (1=Female) * Exposure to flooding	6.33 (9.45)	6.91 (8.74)	14.82 (9.86)	13.77 (10.00)
Risk perception: dummy for flood sensitivity (1=Very serious problem) * Exposure to flooding	-6.72* (3.83)	-12.35** (5.27)	-11.08 (6.86)	-27.72** (12.80)
Risk perception: dummy for flood exposure (1=Once a year or more) * Exposure to flooding	-7.69 (8.16)	-12.42 (8.65)	-24.04*** (7.28)	-17.00 (10.58)
Life satisfaction * Exposure to flooding	1.08 (3.06)	2.77 (3.47)	0.44 (2.93)	3.97 (4.40)
Number of sources of livelihood * Exposure to flooding	-8.30** (4.07)	-11.10** (4.34)	0.69 (5.91)	-12.49 (9.42)
Distance to the river (log+1) * Exposure to flooding	-0.98 (1.94)	1.33 (2.27)	1.65 (3.55)	0.78 (4.04)
Distance to nearest road (log+1) * Exposure to flooding	-4.44 (6.89)	-3.37 (6.21)	-0.89 (11.04)	0.21 (13.16)
Baseline resilience FE	YES	YES	YES	YES
Village-level FE	YES	YES	YES	YES
Observations	1,052	1,052	925	925
Adjusted R^2	0.24	0.35	0.26	0.37
Residual Std. Error	28.36 (df = 1014)	36.90 (df = 1014)	27.95 (df = 887)	35.62 (df = 887)

Note: The outcome variable in all models is resilience-over-time scores (i.e. area under the curve for SERS over time). Only results of interactions between flood exposure and socio-economic risk factors are shown. Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap (200 replications) shown in parentheses. *p<0.1** p<0.05p***p<0.01

Consistent with Table 8, results from the interactions show that differences between male and female-headed households are even more pronounced for those directly affected by flooding. Effect-sizes are large and statistically significant across all models (though to differing extents), suggesting that flood exposure have strong negative impacts on female-headed households. This finding is similarly supported by qualitative insights from Hpa An, with a number of interviewees noting the challenges faced by female-headed households – widows in particular – in seeking support from relatives and family support networks:

> '*Households that are led by widows face difficulties. Of course, they do. If they ask others for help, no one will come. They do so only when they are paid. Widows are especially in trouble.*' (ID#1, Female, Seamstress)

Another distinction can be seen with regards to perceived exposure and sensitivity to flooding. Resilience-over-time scores for those directly hit by the June floods were significantly lower amongst households that generally viewed flooding as a serious threat, as well as those frequently affected by seasonal flooding. However statistical significance is inconsistent between samples and weighting procedures.

We also find that differences in resilience scores for households with more than one source of livelihood are pronounced for those directly-affected by flooding – similar to results in Table 8. However, the strength of associations (and sign) are inconsistent, with no statistical significance found in the balanced sample. Lastly, households that receive remittance payments during heavy flood exposure fare better than those without (though, again, the association is less pronounced for the fully balanced sample).

3.4. ROBUSTNESS CHECKS AND OTHER TESTS OF VALIDITY

As with any large quantitative analysis, our results come with caveats and assumptions. As such, we run a series of robustness checks to test the impact of different specifications on the paper's main findings. In Appendix B Section 2 we examine a range of potential confounders, including: differences between variants of the SERS module (both in terms of composition of resilience capacities and weighting); mode effects (differences between face-to-face and phone surveys); acquiescence bias; non-response; comparisons with an objective measure of flood impact (using monthly income); and controls for the timing of household-level interviews. Though small differences are apparent throughout, all alternative specifications are largely consistent and supportive of the main findings.

3.5. DISCUSSION

The Hpa An mobile phone panel survey yields a wealth of information on how resilience changes over time and how it is affected in the aftermath of natural hazards. To make sense of the many tests and results presented above we re-focus our discussion on the original research questions.

3.5.1. Do self-evaluated levels of resilience fluctuate on intra-annual time-scales?

Of the three research questions, this is perhaps the easiest to answer. Results from the Hpa An survey clearly show how perceived resilience scores fluctuate over the one-year period of study. The extent of this change is visually apparent in Figures 12a and Appendix B Figure 25. From a high-point in Wave 1 to a low in Wave 4 (three months post floods), mean resilience scores in Hpa An drop by 34% between the two periods before rebounding at Wave 7.

These findings have notable implications for resilience policy and programming. For one, efforts to monitor and evaluate resilience-building interventions should be conscious of the perils of relying on one-off surveys. If resilience can fluctuate sharply from one month to the next, then evaluators must be careful in deciding the time periods for comparison. The issues is perhaps of greater relevant to the non-disaster related contexts, where levels of household are often assumed to be constant in the absence of a shock. One way to help address this would be to encourage more widespread use of panel surveys – collecting data over multiple timescales before, during and after an intervention. Another is to more carefully design studies when inferring causality. This is particularly important when it comes to choosing control groups and ensuring that the time periods of data collection are commensurate (e.g. in large household surveys it is typical to measure different groups one after the other, often with a notable time gap between data collection rounds).

Admittedly the findings apply specifically to resilience as measured subjectively (with all the caveats that come with it). However, the rapid changes in perceived resilience for Hpa An point to an inherent weakness in traditional objective approaches. These often rely on long lists of socio-economic indicators and household assets – things that are easier to see and measure. They also frequently rely on immutable indicators (i.e. those that change slowly over time), such as household assets or livelihood activities. Yet, while this survey suggests that a household's resilience-capacities can quickly change in the face shocks, many traditional indicators are unlikely to change in the shorter-term (as is the case for the income comparison in Appendix B Section 2). This can paint an inaccurate picture of a household's immediate resilience status. Ways to better accounting for this should be urgently sought – perhaps through improved integration of objective and subjective approaches, or more widespread of use of non-immutable indicators.

3.5.2. Do natural hazards impact on perceived resilience over time?

Households' perceived resilience in Hpa An clearly fluctuates over time. Yet, can we infer possible causes for this change? This is a harder question to answer. Given the drop in resilience scores immediately after the flood events, it seems intuitive that exposure to floods could be driving some (if not most) of this. The conclusion is further supported both by the DiD analyses as well as the AUC calculations for resilience-over-time (Table 8). Each suggests that the resilience of directly affected households fared significantly worse in the aftermath of the floods when compared with indirectly affected households.

Yet, a number of other intriguing insights remain. For one, why do resilience scores drop dramatically for both directly and indirectly affected households after the flood events? One reason for this might be that the floods impacted on community assets and infrastructure – like roads or access to local markets. Insights from the qualitative interviews support this claim, with reports of widespread localised impacts. Thus, even though households may not have been physically impacted by the flooding, these indirect impacts may have caused households to report lower resilience scores. It may also reflect that the fact that the survey is a census, with households closely networked: indirectly affected households may be sought to offer support (financial or otherwise) to directly affected households nearby - whether family, neighbours or friends.

More importantly, could other factors such as response biases or seasonal fluctuations be partly driving changes in resilience scores (together with, or instead of the floods)? While we try to account for the former by randomising questions and ensuring that priming effects are kept to a minimum, we can do little to account for the influence of the latter in the absence of multi-year data. However, so long as seasonal fluctuations and wider shocks are systematic across the population, they should not change the fact that significant differences are observed between directly and indirectly affected groups (as measured by the DiD estimates). Indeed, the fact that the pattern of gaps is consistent with expectations (starting off large and appearing to converge slowly over time) provides some reassurance of the role of flooding in influencing resilience scores. Moreover, when we exclude households that report other socio-economic shocks during the course of the survey, we see few differences – further discounting the role of wider shocks as playing a large role.

Perhaps the most interesting finding from the study is insight into the length of post-flood impacts. Not only do we see scores fall immediately after the floods, we witness a large up-tick in levels of resilience roughly five months after the baseline surveys (Wave 5). A similar pattern is seen when comparing the differences between directly and indirectly affected households over time (though slight differences in timing for weighted and unweighted samples). Insights like these can prove invaluable guidance for development and humanitarian actors in understanding the extent and nature of recovery on the ground, as well the length of time that households may be susceptible to the impacts of follow-on shocks.

Lastly, we look at whether there are differences in the extent to which the three resilience-related capacities used in devising the SERS module influence post-flooding outcomes. To examine this, we re-run the main difference-in-difference setup (as per Equation 1) replacing the SERS outcome variable with each of the three capacities included in the 3A framework for resilience (Bahadur et al. 2015): anticipatory capacity; absorptive capacity; and adaptive capacity (see Annex B Table 18 for wording). Results are shown in Appendix B Table 27 (models 1-6), revealing that scores for each of the resilience-related capacities drop for households directly affected by the floods (when compared with those only indirectly affected).

Differences are statistically significant for all models (except for anticipatory capacity in the IPTW weighted sample). These findings provide interesting conceptual insights into the extent to which difference components of resilience change both over time and in response to a natural hazard. More specifically, they suggest that each of the three capacities used in the 3A variant acts (relatively) uniformly in influencing resilience-over-time in Hpa An. For comparison, we carry out additional DiD analyses (Appendix B Table 27, models 7-8) using transformative capacity as the outcome variable - noting its use in a number of other resilience frameworks (including Béné et al. 2014 and Pelling 2010). The effect of direct flood exposure is similarly negative for transformation, though not shown to be statistically significant. However, when we re-run the main DiD with SERS scores calculated using the AAT variant (made up of absorptive, adaptive and transformative capacities) in Appendix B Table 28, we find similar negative and significant outcomes – significance drops somewhat for the IPTW sample.

Together with findings in Appendix B Table 21, these results suggest that while individual capacities may differ somewhat (particularly in comparing scores over time), alternative resilience frameworks appear to produce similar outcomes (whether the 3As or the AAT variants). Indeed, this matches findings from Jones and D'Errico (2019) that show how different variants of the SERS module produce similar resilience outcomes in a cross-sectional survey in Northern Uganda. The reduced effect size and lack of significance for the transformation DiD (Appendix B Table 27, models 7-8) is especially interesting, and may reflect the fact that households' ability to transform relates more strongly to underlying issues of power and agency (Carr 2019). These are factors that are undoubtedly entrenched, and unlikely to be altered by exposure to seasonal flooding. We hope that further research, through both quantitative and qualitative means, can be used to shed light on these issues going forward. This includes better targeting of subjective questions to reflect issues of power as it relates to transformation (and resilience more generally).

3.5.2.1. Does exposure to subsequent shocks affect perceived resilience scores?

The SERS module is meant to measure the ability of a household, at any given moment in time, to deal with a range of (hypothetical) future threats. Accordingly, it is not necessarily a measure of the length of time it takes for households in Hpa An to bounce back from the initial period of flooding (though it may be seen as a proxy for this). Rather, SERS measures the extent that households are able to deal with subsequent threats in the aftermath of the floods – whether in the form of further flooding or wider socio-economic shocks. As such, we might expect that any follow-on shocks experienced by households are likely to exhibit further negative impacts on SERS scores. This is especially the case for those directly affected by the initial floods. Testing this is inherently difficult, particularly considering the small sample size of households directly affected by initial flooding. Indeed, the group affected by both June flooding as well as any subsequent shocks totals only 17 in number.

Despite this, we can explore parts of this hypothesis by making use of follow-up questions asked during the Hpa An survey. For example, after the main period of flooding, all households were asked whether they had been affected by any socio-economic or environmental shocks in the period since the last survey Wave (see Appendix B Table 20 for wording). While exposure to follow-on shocks was relatively uncommon (comprising less than a quarter of households over the course of the entire panel), interesting insights can be learned by comparing the impacts of subsequent shocks on resilience scores between households directly and indirectly affected by the initial floods.

To do so, we carry out two additional tests for heterogeneous effects. The first is to augment Equation 4 with an interaction between flood exposure and a dummy for whether the household was affected by a shock in the subsequent waves (similar to the setup in Equation 5). This measures differences in the resilience-over-time score (i.e. the area under the curve for resilience scores) between those affected by subsequent shocks for households directly affected by flooding (compared to those indirectly affected). A second approach is to run a difference-in-difference-in-differences setup (akin to triple-differencing). This essentially augments Equation 1 by adding a further interaction to the original difference-in-difference estimate (see Appendix B Section 3 for equations and full results). Both are similarly interpretable, with the former comparing resilience-over-time scores, and the latter comparing differences in SERS scores directly.

Results from both tests in Appendix B Section 3 show that subsequent shocks are negatively associated with resilience (as seen by the negative coefficients in Appendix B Tables 29 and 30). The association is statistically significant (at $p<0.05$) for the first approach, though not for the triple differencing setup. While inconsistencies in the strength of the associations between the two tests suggest that care should be taken in deriving firm conclusions, the negative effects across all models provide some reassurance that SERS may be: i) responsive to successive external threats (and not just a measure of how long it takes to bounce back from a single event); ii) and responsive to different types of threats. However, limitations in group samples means that follow-up work is needed to establish the nature and strength of these underlying assumptions.

3.5.3. Which social groups fare better or worse in the aftermath of a natural hazard?

There are two factors to consider when examining which groups fared better or worse in the aftermath of the Hpa An floods. Firstly, we can look at the fate of all households in the sample - combining both directly and indirectly affected households. Here, Table 8 points to significant associations between resilience-over-time and: age (older respondents fare better); levels of poverty (poorer households are less resilient); gender of household head (female heads are worse off); higher life satisfaction (happy respondents are more resilient over time); livelihood type (farmers are better off compared with non-farmers); livelihood diversity (those with more sources of income fare comparatively worse); flood sensitivity (those that view flooding as a serious problem are negatively affected); and distance to nearest road (those further away from a road being worse off).

One interesting finding is that the number of household occupants has a significant positive association with resilience-over-time scores (though with a modest effect size). This link is not well explored within the resilience literature, and may reflect the fact that larger households are likely to have more developed social networks and higher human capital available to them. It may also suggest that development actors consider targeting smaller (and likely younger) households in seeking to prioritise vulnerable groups.

It is also interesting to see that education exhibits a weak statistical relationship with resilience-over-time. Moreover, while poverty levels are seen as significant across all unweighted samples, associations in the IPTW sample are inconsistent. These findings conflict somewhat with traditional measurement frameworks that typically assume that higher education and wealth are some of the strongest predictors of resilience (D'Errico and Di Giuseppe 2018). Yet, the survey findings are consistent with previous subjective assessments in other contexts, such as Béné et al (2016) that carry a multi-country comparison and Jones and Samman (2017) that conduct a nationally representative survey of Tanzania. It is also worth noting that education and poverty likelihood are strongly associated with baseline resilience scores (see Appendix B Table 19), suggesting that any lack of association may be in relation to flood impacts rather than stabilised resilience levels.

A second way to look at the results is to focus specifically on the plight of households directly affected by the floods (see Table 9). In many ways this question has more policy relevance: these are households that face the worst consequences. Any differences are therefore more likely to be caused by the floods themselves, rather than being drowned out by the wider sample. Here, two points are noteworthy. First is that female-headed households fare considerably worse than male-headed households (with effect sizes large compared with other household traits). Together with the qualitative data collected, it points to challenges that female-headed households face in gaining access to valuable support networks, capitalising on livelihood opportunities and having a voice in community-level recovery efforts (Islam, 2017).

A second interesting observation is that livelihood diversity (defined as the number of sources of income) is negatively associated with resilience-over-time. The link is statistically significant for both the full sample (Table 8) and the interaction with flood exposure for the partially balanced sample (Models 1-2 of Table 9). In other words, households with a single source of income appear to be better off than those with multiple sources (when controlling for a range of other factors). These findings conflict somewhat with traditional assumptions of resilience and disaster recovery (Adger et al. 2005b; Allison and Ellis 2001). The underlying reasons for this are unclear, though may suggest that promotion of a variety of livelihoods may be an inefficient means of supporting households in recovering from floods (at least in the context of Hpa An). It also adds weight to the conclusions of Liao et al. (2015) that challenge the orthodox of livelihood diversification as applied in the context of Chinese pastoral households. However, we are careful to note that the association between the livelihood diversity and resilience-over-time when interacted with flood exposure is not significant in the fully balanced panel (as per Equation 5 and Table 9). Further evidence – particularly drawing on qualitative insights – is needed in drawing firm policy conclusions.

Lastly, we highlight the importance of strong associations between measures of risk perception and resilience-over-time (particularly when interacted with flood exposure). In essence, this implies that households have some grasp of the factors contributing to their own resilience. More importantly, given that risk perception was measured during the baseline survey (prior to the floods), it may suggest that perceptions of risk (particularly flood sensitivity) have some predictive power in both determining levels of resilience-over-time as well as distinguishing between households likely to be hardest hit by natural hazards. While this has considerable implications for measurement efforts, more can be done to further explore these links, particularly with regards to causal drivers – noting that risk perception is likely to play a role in people's evaluations of resilience (Béné et al. 2019).

3.6. CHALLENGES AND WAYS FORWARD FOR RESILIENCE MEASUREMENT

By combining subjective evaluations with mobile phone surveys, insights from the Hpa An panel survey are an important first step in better understanding (and quantifying) how resilience changes over time. Our findings confirm the well-documented influence of a range drivers for resilience and post-disaster recovery. They also challenge a number of long-held assumptions. To get a better sense of the implications of these findings, as well as whether they apply in contexts outside of Hpa An, a number of research gaps and avenues for further exploration need addressing.

For one, further testing of the validity of subjective assessments and comparisons with the wide range of existing objective approaches is crucial (building on earlier work by Clare et al. 2018 and Jones and D'Errico 2019). In particular, a better understanding of the impact of various cognitive biases on subjective responses will aid in drawing firmer conclusions on the outcomes of perception-based surveys such as this. This includes further exploration of the potential role of psychological adaptation in explaining recovery of SERS scores – similar to the effects experienced in measures of subjective wellbeing (Dolan 2008). In addition, more consistent collection of longer-term panel datasets (from a variety of different contexts) will be crucial in helping to disentangle causal effects, and discounting any confounding influences on resilience outcomes (such as seasonal or mode effects).

With all of this in mind, the results here point to the considerable potential for subjective and mobile-survey tools. The simplicity of their use, cost-efficiency and near-real-time nature of remote evaluation may provide a valuable complement to existing approaches for monitoring and evaluation. If household resilience does fluctuate over shorter timescales (as suggested by the Hpa An survey) then development and humanitarian actors should take note in accounting for this in their vulnerability assessments, project design and post-intervention evaluations. This is particularly relevant in the aftermath of a natural hazard where resilience-capacities are likely to change rapidly. Greater innovation in designing and applying resilience measurement tools that can capture momentary, transient and longer-terms changes is needed. Doing so may be key to ensuring more effective resilience-building interventions on the ground.

Chapter 4

Weathering tough times

Fluctuations in resilience are associated with shifts in seasons and weather

Lindsey Jones

Understanding how resilience changes over time is key to designing effective development and humanitarian interventions. Qualitative insights point to the potential for a household's resilience to vary across seasons, driven by a range of environmental and socio-economic factors. Yet, little in the way of quantitative evidence exists to support these claims. Most quantifiable measures of resilience are ill-equipped to detect short-term fluctuations in resilience, owing to a sparsity of repeat observations and heavy reliance on immutable proxy indicators. To shed light on this issue, I put together a novel high-frequency mobile phone panel dataset. Self-evaluated levels of household resilience are continually collected over two separate years in Hpa An, Eastern Myanmar. Using the panel, I reveal statistically significant differences in levels of perceived resilience between the area's three seasons (hot, dry and rainy). I then match individual surveys with ground- and satellite-based weather observations, showing how perceived levels of resilience are associated with changes in prior weather conditions (both absolute values and anomalies relative to the historical record). Findings point to the need for development actors to pay closer attention to intra-annual changes in resilience. This includes tailoring resilience-building activities to different seasonal needs and recognising the potential for seasonal and weather-related tipping points. Development practitioners should also be conscious of the implications of seasonality in monitoring and evaluation of resilience-building interventions.

4.1. INTRODUCTION

Identifying factors that influence household resilience is crucial to guiding resilience-building efforts. These insights help development and humanitarian actors to target vulnerable groups and protect gains made by resilience-related investments. To date, much of what we know about household resilience comes from qualitative observations, a large portion of which is focused on the Global South (Marschke & Berkes 2006; Akamani & Hall 2015; Tuler et al. 2008). This extensive body of evidence points to an array of factors that influence resilience, including: socio-economic (Berman et al. 2015; Ofoegbu et al. 2017; Barua et al. 2014); ecological (Jabeen et al. 2010; Deshankar 2012); cultural (Nelson and Stathers 2009; Cannon & Muller-Mahn 2010); and psychological characteristics (Béné et al. 2016b; Jones and Tanner 2017).

The climate and weather also play important roles in shaping resilience. For a start, long-term changes in temperature and rainfall can have direct (and indirect) impacts on a household's ability to survive and thrive (Osbahr et al. 2008). The same is true for weather and extreme events: floods and droughts may significantly hamper the ability of households to cope with current and future risk (Wineman 2017; Bhatta & Aggrawal 2016). Accordingly, while we have some insight into the links between long-term climate and resilience, little is known about the roles of seasonality and weather in shaping levels of resilience within a given year – especially from a quantitative point of view. The implications of intra-annual fluctuations are considerable. Not only might they require resilience-building interventions to be tailored to unique seasonal (or sub-seasonal) needs, they have the potential to confound monitoring and evaluation efforts – particularly if evidence is collected across different seasons.

There are two key reasons for a gap in knowledge. Firstly, most resilience measurement tools are ill-equipped to pick up on intra- (and even inter-) annual shifts. In many cases, resilience is measured by tracking changes in wellbeing outcomes in response to given shocks. Resilience is inferred if a household maintains levels of wellbeing above a given threshold. Yet, disentangling any changes in households' capacity to deal with risk is limited by the occurrence of shocks: little can be inferred in the periods in-between. Other approaches focus on indirectly measuring resilience-related capacities as outcomes in themselves. Yet these are often heavily dependent on immutable proxy indicators: ones that seldom (or slowly) change over time (Schipper and Langston 2015). For example, the popular Resilience Index Measurement Analysis (RIMA) features indicators relating to: i) whether households own land or housing property; and ii) whether household members have engaged in casual labour in the past 12 months (FAO, 2016). While these factors are undoubtedly linked to a household's longer-term resilience, they are unable to pick up on any intra-annual properties of resilience – whether over the course of a year, month or week.

A second reason for a gap in knowledge is that the majority of quantitative evidence on resilience comes from one off snap-shots: interviews, discussions and surveys carried out at one moment in time. While there is a growing body of evidence (Allinovi et al. 2009;

Constas and Barrett 2013), few measurement exercises make use of panel data with repeated observations collected over time. Fewer still have gathered information over multiple time periods within a given year (with the exception perhaps of Smith et al. 2015 and Knippenberg et al. 2019).

By collecting high frequency data on household resilience this paper provides fresh insights into whether resilience fluctuates intra-annually, and the factors that might be driving it. More specifically, the paper explores two key areas of interest. Firstly, whether self-evaluated levels of household resilience fluctuate across seasons. And secondly, whether shifts in key weather variables are linked with changes in perceived resilience. Given intricacies of the various relationships, and limited available data, this case study constitutes a first step at a detailed exploratory analysis. Further qualitative and quantitative evidence will be required to uncover the nuances of any potential causal relationships.

I probe these two queries by matching information from two independent datasets. One is a unique mobile phone panel survey of the resilience of 1,203 households in Eastern Myanmar. The panel tracks continual changes in subjectively-evaluated household resilience spanning ten separate survey waves. The other is a dataset of daily weather summaries gathered from a combination of nearby ground-based and satellite observations. By combining timestamps from the two datasets, and exploiting seasonal and daily variation in weather, this paper takes a quantitative looked at links between resilience, seasons and weather. Finally, the implications of key findings for development actors are discussed. In particular, I explore how practitioners can tailor resilience-building interventions to better account for rapid fluctuations in household resilience in both programming and evaluation.

4.2. CONCEPTUALISING AND MEASURING RESILIENCE

In its broadest sense, resilience is a relatively straightforward concept. It is the capacity of a system to retain core functions in the face of disturbance(s), while maintaining options to adapt (Nelson 2011; Carpenter et al. 2001). In practice there is little consensus on an exact definition (Bahadur et al. 2013). Nor is there agreement on how it should be measured (Cutter 2016). Part of the challenge is that resilience is not directly observable (Brenkert & Malone 2005). Instead, resilience is commonly conceptualised as comprising a range of capacities that are in-and-of-themselves intangible (Brenkert & Malone 2005; Schipper and Langston 2015). This diversity in how resilience is viewed means that measurement efforts need to consider two important points.

The first is what a given system is resilient to. Resilience is often thought about in relation to a specific threat. There are numerous examples of measurement toolkits tailored to a single hazard such as droughts, floods or wildfires – amongst many others (Jordaan et al. 2018; Kotzee et al. 2016; Prior and Eriksen 2013). However, it is important to recognise that the impacts of one hazard often interact and combine with other shocks and stresses (whether environmental, social or economic) (Oddsdóttir et al. 2013). This is especially relevant in the context of slow onset events where the threat can evolve over a number of years (Miller et al. 2010). Moreover, many of the underlying drivers of resilience overlap considerably when comparing a system's ability to cope with one hazard or another. As such, measurement frameworks increasingly seek to factor in multi-risk environments (Kappes et al. 2012). This can either be in the form of a collection of related hazards – such as climate resilience or natural hazard resilience – or resilience to risk overall (Oddsdóttir et al. 2013). The same broad focus is the one adopted for the remainder of this paper.

A second point for measurement to consider is how does resilience evolve? Resilience is certainly not static. Instead, the resilience of a social system can be thought of as continually in flux: varying across time depending on the status of the capacities that support it (Keck and Sakdapolrak 2013; Waller 2001). Gradual changes in the capacity of people and communities to respond to threats often arise from the strengthening (or weakening) of development outcomes. These can span multiple years (Sovacool et al. 2012; Adger et al. 2011). Yet, limited attention within the resilience measurement community of practice has thus far been paid to whether resilience fluctuates on shorter-term timescales (Schipper and Langston 2015).

This latter issue brings up the related challenge of how resilience should be tracked. Resilience is inherently a latent process and cannot be directly observed (FSIN 2014). As such there are a number of different ways to go about inferring it. One method is to is to look at how wellbeing outcomes are affected by shocks over time. An example might be to track household income or food security in the aftermath of drought (or any other shocks). Those able to maintain levels of wellbeing above a certain threshold would be considered resilient; those below would not. An index can then be devised to reflect the probability of wellbeing outcomes being above (or below) an allocated threshold. This setup is similar to one proposed by Cisse and Barret (2018), aptly named the 'moments-based approach'.

As second approach considers resilience to be a function of the length and persistence of shocks affecting a given household. Knipperberg et al. (2019) use this approach, providing an illustrative example:

"*Imagine two households experiencing the same shock in a given month; in the next month, if one household is still experiencing the effects of the shock while the other has fully recovered, then the latter household is more resilient. All else being equal, the greater the shock's persistence, the lower the household's resilience to that particular shock*" Knipperberg et al. (2019:6)

Using reports of perceived recovery, they calculate the probability of a household's ability to bounce-back from a given shock over time. In fact, Knipperberg et al. (2019:6) calculate resilience using both the persistence- and moments-based methods with data targeted at food-related outcomes in Malawi.

While these approaches have considerable value, they also have limitations. For a start, they require a shock to have occured before levels of resilience can be inferred. This makes it very difficult to measure resilience in periods where no apparent threats take place. Given that shocks rarely affect households uniformly, it is also challenging to account for variation in exposure and sensitivity within the observed sample. More importantly, it is not easy to use outcome- or impact-based measures to infer whether levels of resilience have changed, as multiple time periods are needed to evaluate resilience within a set period.

A third group of methods takes an altogether different approach. Rather than tracking wellbeing outcomes over time, they seek to indirectly infer resilience. This is typically done by breaking resilience down into core capacities: from anticipatory and absorptive capacities to adaptation and transformation (Berman et al. 2012; Pelling 2010). Markers are then assigned to measure each, before being compiled into a single metric (Brenkert & Malone 2005). Often this happens through use of proxy indicators. These can be identified through expert elicitation or a combination of qualitative and quantitative ground-truthing exercises designed to match desired resilience outcomes with suitable indicators (Bahadur and Pichon 2017). For example, approaches by D'Errico & Giuseppe (2014) and Hills et al. (2012) use a wide range of socio-economic variables as proxies for resilience-related capacities. These are then amalgamated to determine the status of a household's capacity in dealing with future threats.

Seen in this way, resilience is reframed as the outcome of interest. One that is driven and influenced by changes in livelihood and wellbeing outcomes themselves (rather than the other way around). Using this approach, the status of a household's resilience can be measured at any given moment in time. It may therefore be better suited to tracking changes in resilience that may have occurred over a given timeframe (assuming that its chosen constituents are an accurate reflection of the household's 'true' resilience). It is for this reason that I use a capacity-based approach in the main analysis of this paper.

Despite the advantage of capacity-based approaches in measuring changes in resilience over time, few quantitative studies have so far done so. Much of the reason for this owes to the considerable expense of collecting repeated survey information. Yet, understanding the temporal dynamics of resilience has important implications for development practitioners. For example, the design of resilience-building interventions can benefit significantly from knowing whether levels of resilience fluctuate across seasons? Or if resilience is associated with shorter-term drivers like anomalous fluctuations in weather conditions?

From a conceptual point of view the links are decidedly clear. For a start, seasonality and weather are inextricably tied to livelihood outcomes. These in turn strongly determine a household's resilience-related capacities – particularly for households in the Global South (Deveroux et al. 2013). These effects are especially pronounced during extreme weather events:

"*The experience of a disaster is likely to reduce adaptive capacity both in short and longer timeframes, particularly due to limited access to or destruction of resources and capabilities, thus providing additional challenges for future adaptation.*" (Linnenluecke 2012: 28)

From a theoretical point of view, the potential impacts of weather on resilience-related capacities (both direct and indirectly) are manifold. Extreme weather events can inflict large negative impacts on households, particularly through degradation and depletion of assets. They may also require temporary (and in some cases permanent) relocation (Badjeck et al. 2010). At the community-level, Walker et al. (2004) describe how weather-related extremes often serve to erode societal order and degrade critical infrastructure, further lowering the resilience of affected households within. Recurrent hazards can play a similar role in reducing resilience capacities by repeatedly compounding negative development outcomes (Bernhadrt & Leslie 2013).

However, the impacts of weather on resilience-capacities are not limited to extremes. Gradual changes in seasonality and weather directly impact on agricultural and economic productivity – key contributors to livelihood outcomes, food security and the accumulation of household assets in agrarian societies such as Hpa An (Deveroux et al. 2013). Indeed, a household's development outcomes can change considerably from one season to the next (Chambers et al. 1981; Longhurst et al 1986; Cunguara & Kelly 2008; Devereux et al. 2013). In agrarian contexts, much of this results from the timing and extent of rainfall, with knock-on implications for the harvesting cycles of key crops (Silva & Matyas 2014). Other seasonal factors such as shifts in temperature, humidity and wind can have similar impacts on household productivity and wellbeing within a given year – influencing the ability of households to deal with current and future risk. (Longhurst et al. 1986).

Accordingly, while the links between resilience and seasonality have strong theoretical underpinnings, little in the way of quantitative evidence is available. This is particularly so for household-level dynamics. Perhaps the most in-depth look at links between resilience and weather is D'Errico et al. (2019). They examine how temperature shocks (i.e. large deviations in observed annual temperatures) affect household food consumption across 13 years of data using a 'pseudo panel'. Results reveal interesting 'resilience thresholds', with temperature shocks inducing significant negative outcomes for those below a critical level of resilience. While this provides interesting insights, their emphasis is on the impacts of temperature on food consumption (mediated via resilience), rather than on the impacts of temperature on resilience capacities directly. Moreover, given that the surveys are carried out over a number of year, it tells us little about any intra-annual fluctuations. Answers to these questions require higher-frequency data, something that few development agencies have sought in their monitoring and evaluation activities to date.

4.3. METHODS

To shed light on the relationship between resilience, seasonality and weather, I combine information from two independent datasets: i) a high-frequency mobile phone panel survey of perceived levels of household resilience in Hpa An, Myanmar; and ii) daily weather readings from ground- and satellite-based observations.

4.3.1. Mobile phone panel survey of household resilience

Data on household resilience is taken from the Building Resilience and Adaptation to Climate Extremes and Disasters (BRACED) panel survey in Eastern Myanmar. The survey tracks indicators of livelihood opportunities and household resilience from 1,203 households in Hpa An, Kayin district (for further methodological details on the survey see Jones 2019). Information was amassed across ten separate survey waves from June 2017 to November 2018, with consecutive waves occurring every 6 to 8 weeks. To collect baseline information, a face-to-face survey was conducted with heads of all households[19] across eight villages in Hpa An - effectively constituting a census. Basic socio-economic information for the household was gathered including data on household assets, livelihood opportunities and demographic information for all household members.

Upon completion of the baseline survey, each respondent was handed a mobile phone and a solar array for charging. A call centre was then set up in Yangon, with household heads contacted remotely via the headsets provided (or any alternative numbers in the household). Individual identification questions were asked at the start, with surveys lasted 10-15 mins. A small financial reward ($0.5) was provided upon successful completion of the survey. High response rates were maintained throughout the panel – with attrition of only 5% of the original sample after nine successive waves.

To assess changes in household resilience the panel uses subjective-evaluations of resilience. Perception-based measures have been explored by a number of recent studies (Marshall and Marshall 2007; Lockwood et al. 2015; Nguyen and James, 2013; Jones and Samman 2016; Béné et al. 2016a; Jones and D' Errico 2019; Knippenberg et al. 2019). As opposed to 'objective-evaluations' that rely on external observations, subjective-evaluations draw on people's insight into their own resilience (Jones and Tanner 2017; Jones 2018b).

While subjective approaches are not without their own flaws (see Maxwell et al. 2015 and Jones 2018b), they do offer a unique opportunity to draw on bottom-up evidence from respondents themselves (Claire et al. 2017). More importantly, subjective-evaluations allow for transitory changes in household circumstances to be captured that would otherwise be difficult to track using traditional objective methods. For example, while moderate flooding may not damage physical property (and hence would not be tracked by objective measure heavily tied to household asset inventories), subjective-evaluations can more easily pick on deviations in livelihood opportunities, social networks,

[19] In the context of the Hpa An sample, most households were headed by a couple (typically a male and female). In such cases, selection was randomised between the couple to ensure gender diversity.

community cohesion and other intangible drivers of resilience so long as they are adequately factored into the design of the module (Marshall and Marshall 2007; Jones 2018b).

For the purposes of this study I focus on a particular unit of interest: the household. I also adopt BRACED's '3As' framework for defining and characterising resilience (see Bahadur et al. 2015). Here resilience is depicted as comprising three core capacities: i) anticipatory capacity – the ability of a household to anticipate and proactively reduce the impact of hazards or stressors; ii) absorptive capacity – the ability of a household to absorb and cope with the impacts of a shock or stress; and iii) adaptive capacity – the ability of the household to adjust to long-term changes in threats and learn from prior events. To measure these capacities, I rely on people's self-evaluations. Use of subjective measures is particularly attractive as they readily allow for temporal variation: questions are focused on assessing momentary states (as opposed to measures tied to wellbeing outcomes), and are not tied to immutable proxies. Care does, however, needs to be taken in considering the influence of various cognitive biases common to all perception-based measures (an issue I return to below).

To measure changes in perceived resilience I use the Subjective self-Evaluated Resilience (SERS) approach (see Jones & D'Errico 2018). The module solicits individuals to rate the status of their household in accordance with questions targeting each of the 3As' resilience-related capacities (see Table 10). Responses are presented using a standardised 5-point Likert scale. These are then numerically converted, and an equally-weighted mean is calculated, providing an overall score for each household. Finally, resilience scores are standardised using min-max normalisation. This results in a resilience score that varies from 0 (not at all resilient) to 1 (fully resilient).

Table 10: List of resilience-related capacity questions used in the Subjectively-Evaluated Resilience Score

Preamble: 'I am going to read out a series of statements. Please tell me the extent to which you agree or disagree with them.' [Read out each statement and ask] 'Would you say that you strongly agree, agree, disagree, strongly disagree or neither agree nor disagree that:'

Resilience-related capacity	Survey question
Absorptive capacity	Your household can bounce back from any challenge that life throws at it
Adaptive capacity	If threats to your household became more frequent and intense, you would still find a way to get by
Anticipatory capacity	Your household is fully prepared for any future disasters that may occur in your area

Notes: For a full list of resilience-related capacity questions and further methodological details of the SERS approach see Jones and D'Errico (2019).

Note that SERS is a measure of resilience to multi-hazard risk; questions do not target one specific threat. Rather they solicit views on the household's ability to deal with any range of potential hazards. Questions are also posed in relation to hypothetical threats either now or in the future. This allows for a household's current resilience status to be gauged – as opposed to other subjective evaluations that focus on the impact of prior events (see Béné et al 2016a; Claire et al 2016).

4.3.2. Factors that influence self-evaluated resilience

In drawing meaning from the study's findings, it is important to understand how people subjectively interpret questions on resilience. Here much can be learned from the wide body of literature of risk perception and wellbeing (Slovic 1987; Diener 2000; Hogarth et al. 2011; Ruin et al. 2007; Sjöberg 2000). In answering the SERS module, respondents are likely to reflect on a number of factors (whether consciously or otherwise). This includes any past experience of threats, knowledge of present and future risk exposure, socio-cultural factors as well as emotive states (Lenz 2002).

With this in mind, we can envisage three core domains that might influence subjectively-evaluated resilience following Schimmack et al. (2000). These include: chronically accessible sources that variably influence resilience – i.e. those that have a momentary impact on a household's ability to deal with risk (as well as recall of experiences from past events); chronically accessible sources that provide a stable influence on resilience – namely reflections on longer-term base capacities, factors that mediate a household resilience and engrained norms; and temporarily accessible sources that affect judgement – those salient only at one particular moment in time (such as environmental cues and an individual's immediate surroundings).

In reflecting on links between climate and resilience, it is the first of these domains (variable influences) that is of most interest to this study. It reflects how weather and seasons mediate drivers of resilience in the shorter-term. These interact and combine with more stable drivers of resilience that seldom (or slowly) vary over time. Yet, it is also important to consider how the last domain (temporary accessible sources) may affect subjective evaluations of resilience – principally those that act as confounders and biases. For example, seasonal shifts and weather extremes may alter moods, which can in turn shape a respondent's judgement on their own capacities and risk appetite (Kampfer and Mutz 2013; Hogarth et al. 2011). It should be noted that literature on links between weather, mood and risk-related self-efficacy is decidedly sparse (Rundmo & Sjoberg 1998; Lenz 2002).

Efforts to establish associations between weather and life satisfaction are similarly mixed (Lukas et al. 2013). Personality may also have a strong influencing factor in subjective judgements. However, because personalities are typically considered constant over time (especially in the context of several months), use of panel data can help to account for this trait by comparing within-individual observations (Cobb-Clark & Schurer 2012). While it is difficult to disentangle the roles played by chronic and temporary sources in evaluating resilience, and flag that findings must be interpreted with this caveat in mind, I do employ a number of methodological strategies aimed at isolating temporary confounders such as mood, time of day and day of week as detailed in Section 4.5.

4.3.3. Weather and seasonal climate observations

To examine the relationships between resilience, seasonality and weather I use daily weather information from an observational station located in Hpa An (WBAN ID: 480990 99999). Publicly accessible data are gathered through the National Climate Data Centre (NCDC), with daily weather summaries available for a range of climate variables (https://www.ncdc.noaa.gov/). For the purposes of this analysis, the following variables are used: precipitation; average temperature; maximum temperature; minimum temperature; humidity (measured via dew point); and maximum wind speed.

In generating daily summaries, a minimum of four observations per day must be present with inputs undergoing automated quality control via NCDC. Data for Hpa An range from 1973 to the present day. However, large gaps in the climate record exist – particularly from 1994 to 2012 where no observations were made (likely due to civil conflict that affected the area during this period).

Gaps in daily precipitation data are particularly noticeable during the period of the panel survey. As such, I use alternative values for precipitation in each of the main model specifications taken from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) repository. CHIRPS combines 0.05° resolution satellite imagery with in-situ station data to create a gridded rainfall time series (Funk et al. 2015). For a comparison of CHIRPS and precipitation values gathered from the weather station see Appendix C Section 1.

In addition to weather observations, information on river discharge from the nearby Thanlyin river is obtained from The Global Flood Awareness System (GloFAS). GloFAS combines ensembles of lower-resolution forecasts from ECMWF IFS (Integrated Forecast System) with hydrological models and post-processing algorithms. From this, probabilistic streamflow forecasts at 0.1° are generated and compared with known flood thresholds for a given area (see Emerton et al. 2018).

Dates across all datasets are matched with timestamps for the household panel surveys. As survey enumeration is conducted using Computer Assisted Personal Interviewing (CAPI) software, electronic timestamps are automatically generated allowing for weather observations during the time of each individual survey to be compiled.

4.3.4. Estimation frameworks

In examining links between seasonality, weather and resilience I use a series of fixed effects regression specifications. I start by looking at whether resilience scores differ across seasons by regressing subjectively-evaluated resilience scores (R_{it}) for household i on day t against a season variable (S_s), with dummies corresponding to each of the region's three seasons: the rainy (June-October), hot (March-May) and dry season

(November to February) (Aung et al. 2017). ξ_y relates to dummies for each calendar year, meaning that repeat observations within the year are pooled and averaged. Given that subjective judgements may be affected by the day of the week and hour of the day of interviewing (Csikszentmihalyi & Hunter 2003; Feddersen et al. 2013), I include fixed effects for these in γ_d and $\emptyset_h$ respectively. Crucially, use of an individual fixed effect, α_i helps to account for any time-invariant factors that may influence perceived resilience scores (such as immutable socio-economic characteristics of the household or personality traits of the respondent).

$$R_{ithdsy} = \alpha_i + \beta_1 S_s + \psi_h + \gamma_d + \xi_y + e_{ithdsy} \tag{1}$$

To probe more carefully at the role of fluctuations in weather, I then regress resilience scores against an array of weather variables W_t. More specifically, W_t is calculated as a 3-day rolling average of mean daily observations for precipitation, temperature, minimum temperature, logs of maximum wind speed and dew point. For example, W_t is the mean weather reading (∂) for the day of interview and two days prior (*t, t* - 1*, t* - 2). Use of a moving average helps to account for any shorter-term influences of weather on resilience immediately prior to the interview, as well as the fact that interviews may have been conducted early in the day – similar to the setup used in Anderson and Bell (2009). Later I test the main results against a range of moving average lengths to examine the implications of this choice. As maximum temperatures are highly correlated with average temperature (see Appendix C Figure 25) the former is removed from the model. To account for any non-linear relationships, a quadratic for all weather variables is added.

$$R_{ithdsy} = \alpha_i + \beta_1 W_{tdsy} + \beta_2 W_{tdsy}^2 + \psi_h + \gamma_d + \varphi_s + \xi_y + e_{ithdsy} \tag{2}$$

$$W_t = \frac{1}{3}\sum_{j=0}^{2} \partial_{t-j} \tag{3}$$

To ease with visual interpretations of the outputs from Equation (2), I replace W_t (and its squared term) with binned deciles, allowing for effect sizes to be compared across deciles via the coefficient plots in Figures 17, 18, 19. Deciles are calculated with respect to observations during the period of the survey.

To remove the influence of any time-invariant household-level traits I add a household fixed effect, α_i. I also include time fixed effects in the form of year and season dummies, in ξ_y and φ_s respectively. Use of the latter helps to remove any seasonal influences. In addition, I re-run models with month and year fixed effects, to further account for seasonality. Note, however, that this results in an unbalanced sample (as survey waves spanned calendar months on a number of occasions).

Finally, a key challenge for this paper is in disentangling the roles of seasonality and weather on resilience. While use of season and month fixed-effects in the two previous specifications is one away of distinguishing between the two, another is to look at the effects of anomalous periods of weather. For example, unseasonably hot (or cold) spells provide opportune moments to explore whether temperatures have an effect on resilience outside of any seasonal influences. Crucially, these spells are quasi-random and can happen throughout the year, spanning all three seasons.

To examine the effects of unseasonal weather I calculate a series of Z-scores for each weather variable. In essence, these scores tell us how unseasonable the weather is during the period just before the interview, relative to what we would expect based on the historical record for that same period of time. Positive Z-scores indicate periods of above-average conditions, while negative scores are linked with periods that are below-average (relative to the historical record). Given that records for many of the weather variables have large amounts of missing data, I extend the window of interest to feature mean weather conditions for the 6 days prior to (and including) the day of the interview. This essentially constitutes average weather conditions for the previous week.

The Z-score for any given week, Z_t is therefore calculated as a function of the weather during the seven-day period prior to interview ω_t, minus the historical mean of that same period, $\overline{\omega}_t$, divided by the standard deviation of all historical observations for the window in question, s_t.

$$Z_t = \frac{\omega_t - \overline{\omega}_t}{s_t} \qquad 4)$$

I limit historical observations to all available data for the past two decades: 2012 for the NCDC dataset; 2009 for CHIRPS; 1997 for GloFAS. I then re-run the main analysis in Equation 3 replacing weather observations with Z-scores, Z_t. I also exclude wind speed and humidity as control variables as they contain a number of missing data-points in the observational record.

$$R_{ithdsy} = \alpha_i + \beta_1 Z_{tdsy} + \beta_2 Z_{tdsy}^2 + \psi_h + \gamma_d + \varphi_s + \xi_y + e_{ithdsy} \qquad 5)$$

Given the difficulty of using traditional Z-scores for interpreting count data (owing to large skews) I use a modified Poisson-Z score for the rainfall and maximum windspeed variables. Proposed by Wheeler (2015) this is calculated as twice the square root of the average weather during the seven days prior to interview minus the historical mean for the same period.

$$Z_t = 2\left(\sqrt{\omega_i} - \sqrt{\overline{\omega}_t}\right) \qquad 6)$$

This standardised metric is it broadly comparable to a traditional Z-score.

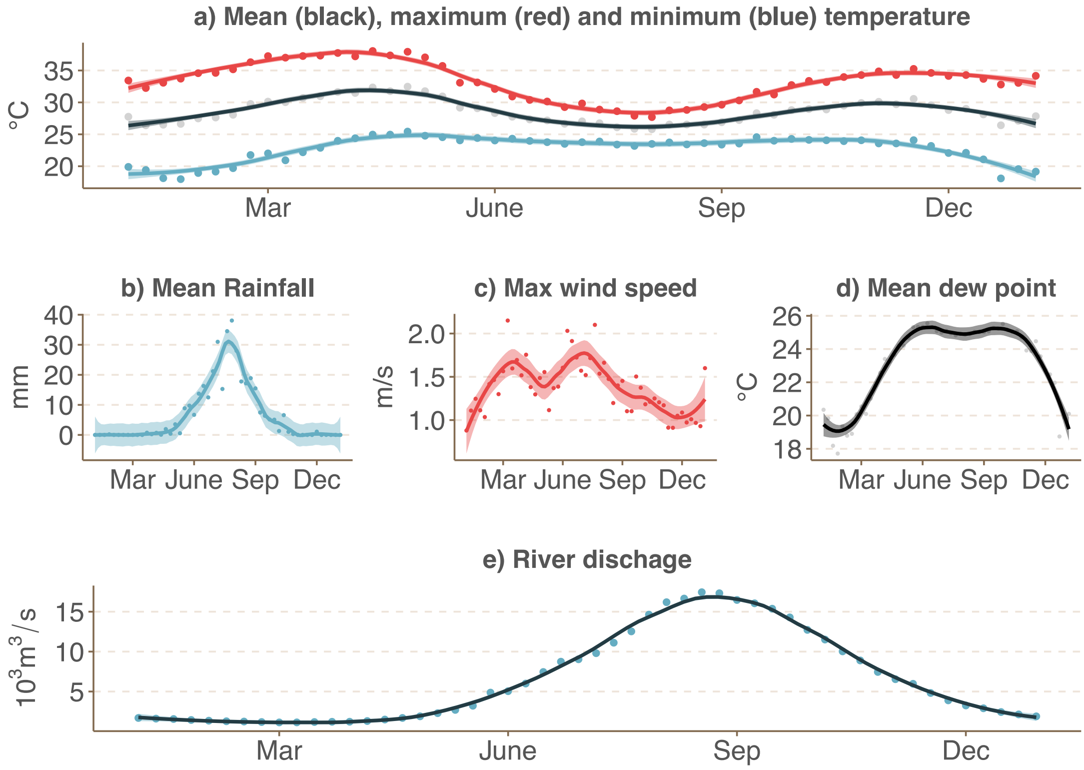
4.4. RESULTS

Before delving into the results from, the regression models, it is important to step back and understand seasonal and livelihood dynamics in Hpa An. As with most areas in Myanmar, Hpa An has a tropical monsoon climate. Daily average temperatures range from 26-32 °C, with spells of temperatures up to 38 °C not uncommon. Hpa An climate is characterised by three distinct seasons, a hot (March-May), rainy (June-October) and cool season (November-February). Almost all of the area's precipitation falls during the rainy season, coinciding with higher levels of discharge in the nearby Thanlyin river – though a noticeable lag can be seen in Figure 15.

Livelihoods in Hpa An are closely tied to water and the local environment. Agriculture remains the mainstay of most households, with 40% of the surveyed population deriving a primary source of livelihood from farming (mostly subsistence). Significant contributions are also sought from casual labour and foreign remittance – typically from individuals seeking temporary employment in neighbouring countries like Thailand. Levels of socio-economic development are low. Only 50% of household heads in the sample have some form of primary-level education, with 30% reporting no formal education at all. Like much of the country, infrastructure and public services are significantly underdeveloped. This is further hampered by protracted civil unrest that has affected the region since 1950, with considerable knock-on implications for the quality of education, health and transportation services. Since 2012 the situation has ameliorated, though political tensions have known to flare on occasion (Bremmer 2018).

While the area is occasionally affected by drought and cyclones, floods are by far the most prominent climate hazard affecting the area – owing to the proximity of the Thanlyin river, and low-lying nature of most villages in Hpa An. Some support for disaster risk reduction initiatives has been received from NGOs and local government in recent years (largely through the BRACED programme), though most households are forced to rely on autonomous coping and adaptation strategies in the face of climate risk (Jones et al. 2018a).

Figure 15: Seasonal profiles of key weather variables in Hpa An

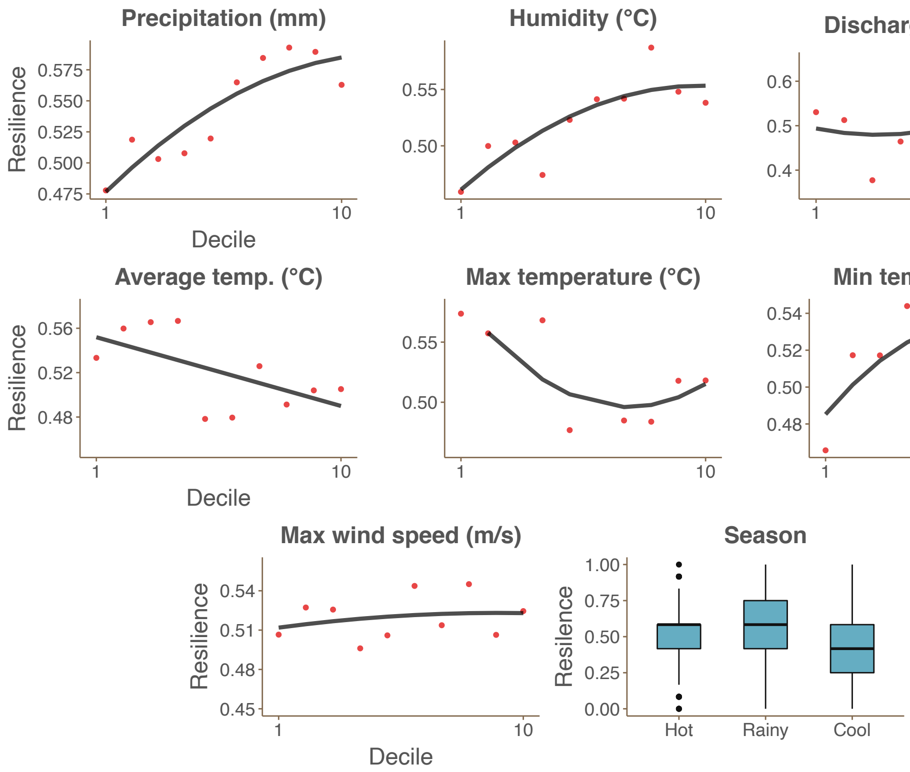


Notes: Figures show weekly averages for climate variables using observations from 1994-present. For river discharge, historical observations run from 1997-present. Lines are loess curves with 95% confidence intervals shaded.

I now turn to investigate factors linked with resilience over time. In particular, I am interested in knowing if shifts in seasons and weather are associated with changes in self-evaluated household resilience over the course of the survey. Figure 16 plots associations between various weather variables and aggregated resilience scores. A clear positive association is seen for precipitation, humidity and discharge: higher resilience scores are associated with rises in mean values for observed weather variables. In most cases the relationship appears non-linear.

Temperature variables also exhibit noticeable relationships. In the case of average and maximum temperatures, the relationships are negative, with higher resilience scores associated with lower temperatures in particular. Interestingly, minimum temperatures show a somewhat different picture, with higher resilience scores linked with higher minimum temperatures. The trend appears to level off at higher deciles. Maximum wind speeds also exhibit a slight positive association, though the trend is weak. Lastly, in pooling resilience scores across seasons we see that resilience scores reported during the hot and rainy seasons appear somewhat higher than for the cool season

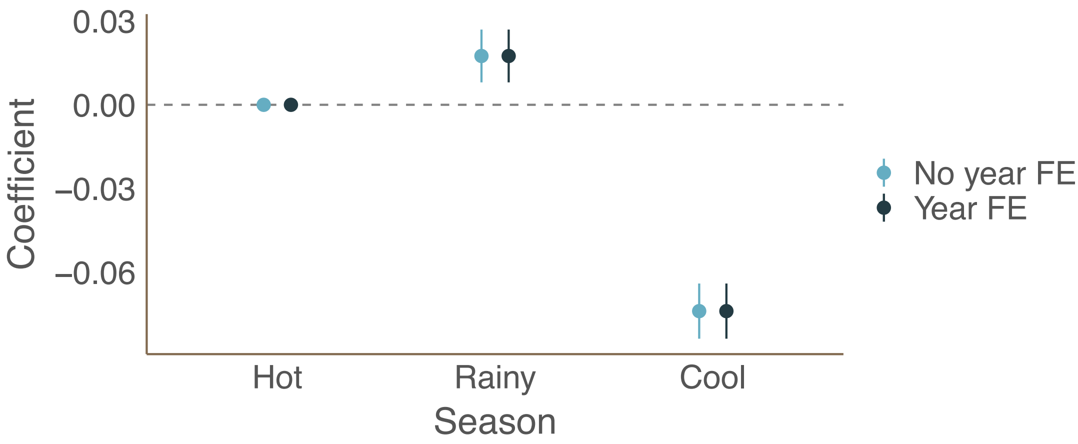
Figure 16: Associations between weather and aggregated resilience scores



Notes: Each panel shows aggregated mean resilience scores for deciles of the weekly weather variable. Quadratic polynomial trend lines are shown for each scatterplot (except for Temperature where a linear trend is shown). Humidity is measured as dew point temperature. The final panel shows mean (black line) and interquartile ranges (box) across Hpa-An's three seasons.

In themselves, these simple associations reveal a great deal about how resilience scores vary in accordance with weather and seasonal shifts. However, it is also important to consider the influence of confounding factors (including influences on yearly and seasonal shifts) before any firm conclusions can be drawn. In so doing, I start by regressing self-evaluated resilience scores against a set of season dummies (Eq. 1). Figure 17 shows the outputs from this model, pointing to higher scores for households during the rainy season, and lower reported values during the cool season. Both time periods exhibit statistically significant differences from the reference period (the hot-season). Results differ little when controlling for differences across the calendar years by including year fixed effects.

Figure 17: Seasonal differences in self-evaluated resilience



Notes: Dots represent beta coefficients for seasonal dummies with the hot season as the reference period following the set-up outlined in Eq. 1. The dark blue model includes year fixed effects, while the light blue does not (akin to a one-way fixed effects model). Horizontal lines are shown as 95% confidence intervals. Standard errors are clustered at the household level.

By itself, knowing that resilience fluctuates across seasons has considerable implications for the design and delivery of resilience building interventions. However, further insight can be gleaned from investigating potential drivers of seasonal variation. One obvious candidate is seasonal shifts in weather. To examine this relationship in more depth Appendix C Table 31 shows outputs from the model described in Eq. 2, examining associations between resilience and a range of weather variables. In order to visually interpret these findings, Figure 18 plots model coefficients of deciles for each of the weather variables of interest.

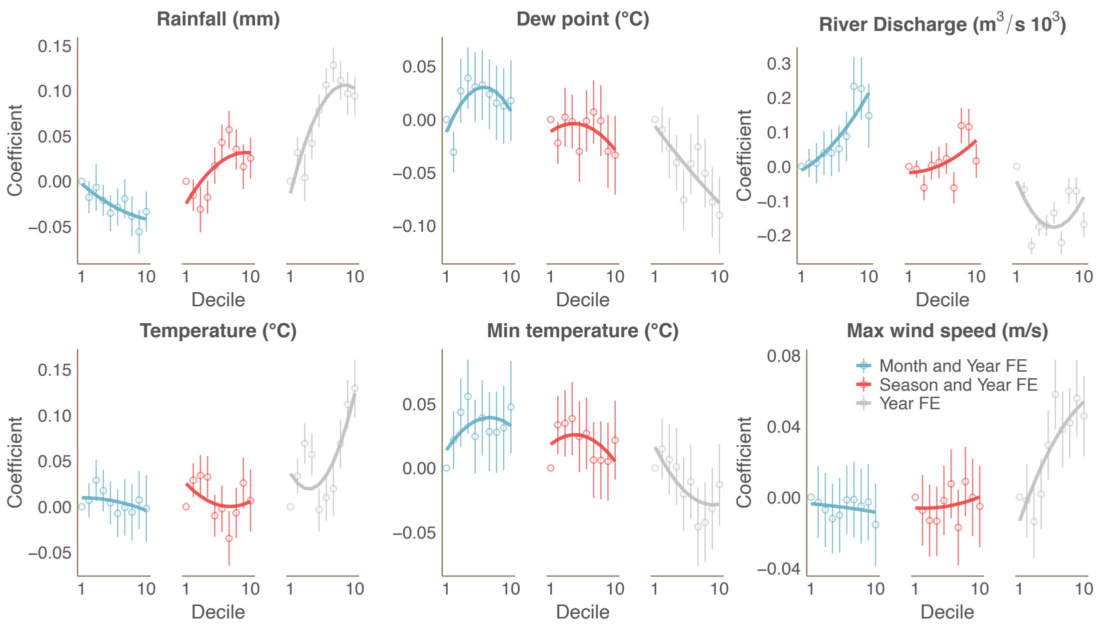
In each case, separate models are run using: year (grey line); season-year (red line); as well as month-year fixed effects (blue line) – corresponding to Appendix C Tables 31, 32, and 33 respectively. Each tells us something different about the various temporal relationships between resilience and weather as it varies across seasons. Year-fixed effects pool household-level observations across separate years, revealing within-year associations between resilience and weather. However, this cannot account for any seasonal differences that may arise (either due to seasonal fluctuations in weather or wider socio-economic factors). Use of season-year fixed effects allows a closer look at within-season associations, helping to remove the effects of seasons from the overall model. Lastly, inclusion of monthly-year fixed effects acts as a second, more fine-grained, method of accounting for seasonal trends – though it comes at the cost of an unbalanced panel and fewer observations per round of observation. Despite this, I retain the model as an interesting point of comparison, particularly in being able to distinguish between seasonality and weather.

As with the simple correlations in Fig. 16, a number of relationships between resilience and weather are clear. In the case of rainfall, we see that periods of high rainfall are associated with higher self-reported resilience across both yearly and seasonal models.

Interestingly, however, the trends level off somewhat at higher deciles, potentially suggestive of non-linearities. Part of this may be to do with negative impacts of excessive rainfall, which can have clear knock-on implications for crop production and livelihood activities. The extent of the effect appears to increase when moving from seasonal to yearly models. However, the within-month model showcases a different outcome. Here a negative trend is observed – though with decidedly weaker effects compared to the other two models. This highlights the importance of distinguishing between the various model setups, as rainfall is largely restricted to a handful of months during the rainy season (as seen in Figure 15). The reliability and meaning of the within-month (and to a lesser extent the within-season) models is therefore diminished in this case – yet important to consider none-the-less.

Associations between resilience and humidity exhibit a negative relationship, with rising levels of humidity associated with lower resilience scores. The effects are especially pronounced for the seasonal and yearly models. The monthly model is decidedly non-linear with a clear inverse-U shaped relationship. Conversely, associations with discharge from the nearby Thanlyn river reveal positive non-linear links. Higher levels of discharge are, by and large, linked with higher resilience. Yet, the trends vary across models. Notably, the yearly model exhibits a U-shaped trend – with higher scores for both lower and higher deciles.

Figure 18: Coefficient plots of associations between resilience and aggregated weather variables



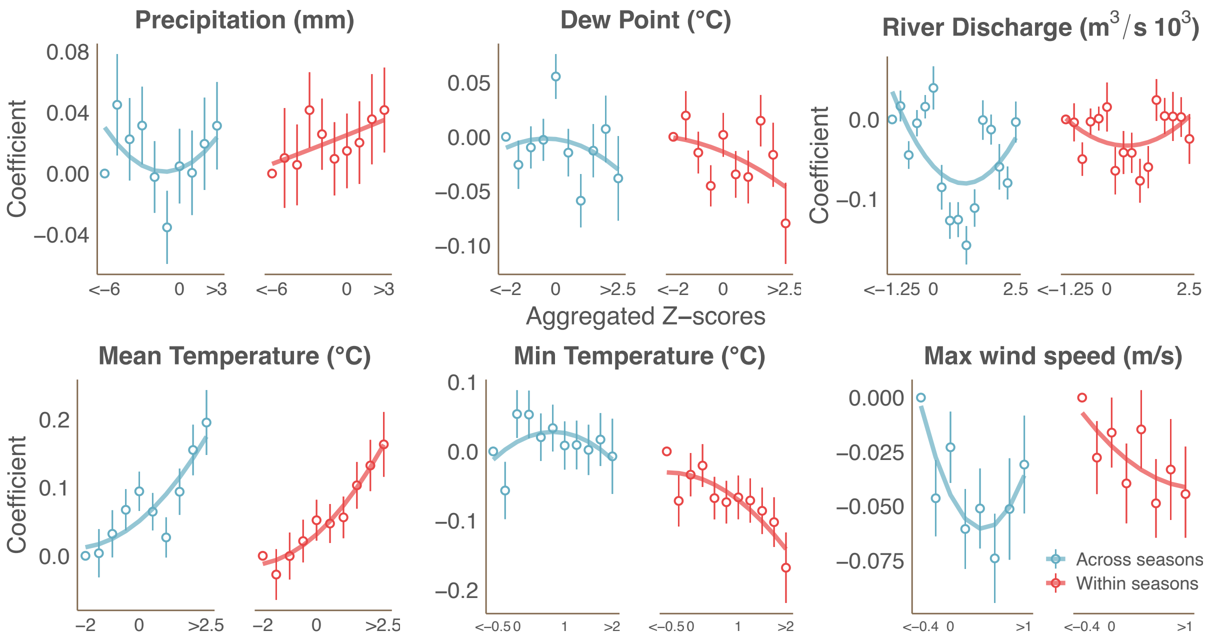
Notes: Plotted outputs match Eq. 2. Panels show results from separate regression models with each respective weather observation replaced by binned deciles (all other variables are identical to the setup in Eq. 2). Dots represent beta coefficients for binned deciles for each respective weather observation, with horizontal lines showing 95% confidence intervals. Outputs in blue include month and year fixed effects, outputs in red feature season and year fixed effects and outputs in grey have year fixed effects. All models include day of the week and hour of the day fixed effects. Lines are shown as quadratic polynomial trends. All regressions feature standard errors clustered at the household level.

The relationship between different temperature variables and resilience also point to different seasonal and intra-seasonal roles. For mean temperature, we see a positive non-linear relationship in the across-season model with higher temperatures linked with higher resilience. Yet, the effects are far diminished for the monthly and seasonal models. They are even suggestive of an opposing negative association – though only statistically significant for the within-season model (Annex C Table 33). Remember here that maximum temperature levels were removed from the regression because of high correlations, making it's difficult to attribute these relationships to one or the other. Similar disparities are also seen for minimum temperatures. In particular, the across-season model shows a strong negative relationship (levelling off at higher deciles). Monthly and seasonal models exhibit weaker relationships. Lastly, maximum wind speeds only has a clear positive association for the across-season model - potentially suggesting a stronger role for the influence of seasonality.

Finally, I turn to associations between perceived resilience and weather anomalies. In many ways, anomalies are a better test of resilience-weather links as they occur quasi-randomly and are less likely to reflect seasonal artefacts. They are also closely tied to extreme weather events, with well documented impacts on household-level resilience – both direct and indirect (Wineman et al. 2017). To measure weather anomalies, I create

Z-scores for each of the variables of interest. These compare weather conditions prior to the interview with average conditions recorded in historical observations. Scores close to 0 can be thought of as 'normal' weather conditions (relative to what we would expect for the given time of year). Higher Z-scores reflect above average conditions, while lower scores are associated with below average. By following the set up shown in Equation 5, I run separate models using across-season (without seasonal dummies) and within-seasonal specification (with seasonal dummies). To help visualise the results I bin Z-scores and plot coefficients as shown in Figure 19.

Figure 19: Associations between resilience and periods of anomalous weather conditions



Notes: Dots represent beta coefficients for binned values of Z-scores for each weather variable. Z-scores for mean and minimum temperature are shown as traditional Z-scores, while those for precipitation, humidity and discharge are Poisson Z-scores. In instances where binned categories have small samples, I collapse them with the nearest bin and indicate them with a '>' or '<'. Horizontal lines show 95% confidence intervals. Outputs in blue include month and year fixed effects, outputs in red feature season and year fixed effects. All models include controls for Z-scores of the other weather variables, as well as day of the week and hour of the day fixed effects. Lines are shown as quadratic polynomial trends. All regressions feature standard errors clustered at the household level.

Results suggest that anomalous weather conditions are similarly associated with changes in self-reported resilience – often in non-linear ways. For example, weeks with above average temperatures are linked with steady increases in subjectively-evaluated resilience; cooler periods are similarly linked with lower resilience. Interestingly, minimum temperatures appear to show an inverse relationship, with higher average temperatures associated with reduced resilience scores (though the effect is more pronounced in the within-season model). In both cases, trends appear to match findings from across-season models in Figure 18.

Interestingly, there is a clear U-shape to many of the weather-resilience links. This applies to the effects of river discharge, wind speed and levels of precipitation (largely for the across-season model). Here both abnormally high (and low) weather conditions are associated with higher resilience, with the nature and extent differing depending on the variable of interest. An inverse-U shape is also apparent for minimum temperatures and humidity – though more prominent in the across-season models for both. Again, many of these seem to broadly reflect trends in Figure 18, particularly for precipitation, humidity and discharge.

It is also worth pointing out that the range of Z-scores for minimum temperatures, wind speed and precipitation showcase slight skews. This may be partly driven by the fact that surveys were carried out in batches rather than randomly assigned throughout the year. It is possible that these periods coincided with slightly warmer, windier and drier spells as compared to the historical record. It is also likely to reflect the fact that Hpa An's climate and local environment has shifted in recent decades owing to a combination of climate change and wider social, economic and environmental factors affecting the region (Aung et al. 2017).

Above all, findings showcase the importance of distinguishing between resilience links with cyclical changes in seasons (i.e. Figure 17), variation in raw weather conditions (Figure 18) and anomalous spells of weather (Figure 19). Though related, each are likely to impact differently on a household's ability to respond to external threats.

4.5. FURTHER ANALYSES AND ROBUSTNESS CHECKS

In testing the various assumptions and findings from the main analyses I carry out three wider tests and checks.

To start with, I address a valid concern that changes in seasonality and weather may be influencing people's affective domain (i.e. the respondent's mood at the time of surveying). These in turn could bias self-evaluations of resilience, artificially creating a link with seasons or weather (where non might be present). This confounder is difficult to account for in the absence of repeated direct measurements of affect. However, it is possible to test the extent to which positive (or negative) affect may be driving resilience scores through use of proxies.

During the course of the 10-wave survey, four separate waves featured modules related to happiness, subjective wellbeing and sense of purpose – each can be considered proxies for momentary positive affect or mood (Studer & Winkelmann 2014). By re-running the main analysis (Appendix C Table 35) with affect-related controls, I find few qualitative differences compared with a similar set-up mimicking the main analysis. Interestingly, all three measures of affect have positive and statistically significant associations with resilience when controlling for weather and seasonality. Though the sample size is considerably reduced, these findings indicate that any confounding influences of mood on self-evaluations of resilience are likely to be minor – potentially ruling out seasonal influences on affect as a cause of the trends documented in the main analysis.

A second area of interest is to look at different associations within seasons. This can be done formally by interacting each of the weather values (W_t and W_t^2) with seasonal dummies (S_t). Appendix C Table 36 presents these results in detail, with statistically significant differences seen for many weather variables. We can also take a more visual look at seasonal differences by limiting Eq. 2 to samples during the hot, cool and rainy seasons. Annex C Fig. 26 shows visuals of binned deciles for each of the weather variables of interest using a model with season-year fixed effects. Here deciles are calculated in accordance with total values within each season (rather than across the entire year).

The first thing to note is that confidence intervals are larger compared to those in the full sample (Fig 18). This is somewhat inevitable given the large reduction in sample size for each model. While many of the seasons show similar trends and associations with self-reported resilience, there are a number of interesting differences. For a start, a weak positive trend between resilience and rainfall is noted during the hot season (perhaps unsurprising given the low levels normally received during this time of year). Yet, during the rainy season the relationship appears as a negative quadratic, with higher rainfall linked with lower resilience scores. This may reflect the fact, while rainfall is generally associated with higher resilience throughout the year, excessive amounts during the rainy season could harbour negative effects.

Seasonal trends for river discharge appear notably mixed: rising levels are linked with higher resilience during the cool season, and to some extent the rainy season (though with a large drop in the higher two deciles). Yet, the hot season exhibits are clear negative trend. Similarly, the influence of temperatures on self-reported resilience are inconsistent across seasons – both for average and minimum temperatures. Interestingly, higher temperatures during the hot season are strongly linked with higher resilience.

In a third test of the paper's core findings, I replicate the main analyses with a secondary independent dataset. As part of the BRACED programme, an auxiliary mobile survey was set-up in Mudon, a town 60 kilometers South of Hpa An. The survey in Mudon was conducted with 767 households, matching the same protocol used in the Hpa An survey. However, the Mudon equivalent was considerably shorter, consisting of just four separate waves (one face-to-face baseline and three mobile phone surveys) from July 2018 to January 2019. As with the main analysis, timestamps for each household survey were matched to a nearby observational weather station – in this case located in the adjacent town of Mawlamyline (20kms away).

Matching the set-up in Eq 2, Appendix C Table 43 reveals a number of associations between resilience and weather (using both monthly and seasonal fixed effects)[20]. The results are strikingly similar to those observed in Hpa An, with significant associations for the seasonal model, including rainfall, temperature, and wind speed. Associations in the

[20] Year fixed effects are removed from the model as the time period spans less than 12 months.

monthly model are notably weaker, again a trait matched with the Hpa An series. Despite the time period in the Mudon dataset being far shorter, the close match between the two independent datasets provides some confidence in the consistency of the paper's main findings.

Lastly, I present a series of further tests and checks detailed in Annex C Section 1. In particular, I: replace satellite-based precipitation values with those from the nearby ground-based weather station; omit wind speed and humidity from the main analyses (owing to high missing values); cluster standard errors at the village-level; examine heterogenous effects across gender and livelihoods; test for different outcomes amongst different resilience frameworks; and look at the implications of different rolling averages (using 1-day, 3-day and 7-day lags).

4.6. DISCUSSION AND CONCLUSIONS

This paper sought to uncover links between intra-annual changes in resilience and a number of potential drivers. In the first step, I showed how self-evaluated levels of resilience differ across Hpa-An's three seasons. Levels of household resilience are highest during the rainy season (June-October), with the lowest reported scores seen in the cool season (November-February). Differences across all three seasons are statistically significant. In the second step, I revealed close associations between resilience and shifts in a large number of weather variables – both across seasons and within them. Again, links for many of the variables are significant, though the extent and nature of the effects differ markedly depending on the set-up of models. Moreover, I showed how weather anomalies (i.e. how far current conditions differ from the historical average) are similarly linked to changes in self-evaluated scores for most variables. Further analyses reveal that these associations are robust to different setups and are broadly replicated using a secondary (shorter) dataset in nearby Mudon.

Before considering the implications of these findings, it is important to think through potential mechanisms and drivers. Fortunately, there is a substantial wealth of wider literature to drawn on. A long history of sustainable livelihoods research has highlighted that seasonality can have a strong influence on household-level development outcomes (Chambers et al. 1981; Longhurst et al 1986). These fluctuations are often indirectly mediated through factors like agricultural outputs, employment opportunities and food security – each of which are at the core of a household's assets and capacities (Devereux et al. 2013). Given the close ties between livelihoods and resilience (Tanner et al. 2015), any intra-annual fluctuations in these contributory drivers are likely to in-turn impact on the capacity of households to respond to present and future risk.

It is thus reasonable to expect that self-evaluated household resilience may fluctuate within a given year (perhaps even on a monthly or weekly basis). Yet, few existing resilience measurement tools are able to pick up on such shifts. In relating results from the analysis back to the three domains laid out in Section 4.4. it is likely that shifts in seasonality and (perhaps to a lesser extent) weather are acting as shorter-term or momentary influences on household resilience. These combine together with more stable influences such as household assets, or livelihood practices that serve as chronically accessible drivers of resilience – unlikely to change in the course of a given year. However, drawing firm conclusions as to the distinction between these different domains is likely to require considerable further evidence.

By looking at links between resilience and shifts in key weather variables over time, we can also explore potential within-season drivers. Significant trends associated with temperature, precipitation, discharge and humidity all point to different potential drivers (both direct and indirect) that contribute to momentary shifts in self-evaluated resilience. Reasons for these links are likely tied to the same underlying drivers underpinning seasonality. Namely, the mediating impacts of weather on household assets and livelihood opportunities – though require use of causal methods and further qualitative exploration to validate assumptions. These links are further supported by evidence in Figure 19 showing how weather anomalies are tied with changes in self-evaluated resilience. Findings are all the more insightful as the SERS module is not hazard-specific. Questions are designed to address multi-hazard risk, with wording devoid of any reference to weather.

Perhaps equally important is to note that many of the relationships between resilience and shifts in weather are non-linear. Most associations are quadratic in nature, potentially suggestive of thresholds and tipping points. This is similar to findings by D'Errico et al. (2019) who identify a temperature threshold for food-security in rural Tanzania. Moreover, we underline the fact that seasonal patterns like these are likely to be highly context-specific. Together these insights can be of considerable use in determining when and where resilience-building activities should be targeted – helping to prevent the design of ill-suited interventions based on insights into seasonal and weather-related trends.

Interestingly, evidence on the degree to which these trends arise as a result of seasonality or within-season fluctuations in key weather variables appears to be mixed. Results from the seasonal interactions in Appendix C Table 36 showcase clear within-season differences. Yet, the fact that models inclusive of month-year fixed effects for Eq. 2 (Appendix C Table 33 and Figure 18) are less-clear suggests that seasonality may be playing a stronger role than shorter-term fluctuations in weather. Again, we note the caveats regarding set-up and efficiency using this model. We also point to the fact that the survey site has a decidedly narrow geographic scope.

Weather observations are the same across all individuals on any given day, meaning that little variation takes places during the course of each wave (and therefore limiting variation at refined scales like the monthly model). Yet, the fact that significant trends are evident when examining the impacts of unseasonable spells of weather (as per Figure 19) does point to a clear role in addition to seasonality. Exploring these traits in more detail requires higher frequency surveys, longer-term panels and data gathering across multiple sites. Doing so will also allow for more advanced time series methods, including autoregressive models and alternative methods for deseasonalising resilience outcomes (Shumway and Stoffer 2017).

A number of study limitations must also be considered before firm conclusions can be drawn. Firstly, the potential for wider unobserved time-varying factors to confound the results of the main analyses. Not only do a range of other socio-economic and environmental factors fluctuate intra-annually, many of these will in turn be influenced by seasonality and weather. This makes it difficult to disentangle which factors are directly responsible for influencing household resilience and the relationships between them. Indeed, this study is an important first step as an exploratory analysis in examining potential links with intra-annual resilience, recognising its clear methodological limitations and scarcity of available data. As findings cannot establish causal relationships with any certainty (nor do they seek to), further qualitative and quantitative evidence will be needed in gaining a more nuanced understanding of these complex dynamics.

Secondly, an important reminder needs to be made that self-evaluations of resilience are inherently subjective. It is therefore difficult to establish whether fluctuations in SERS scores are reflective of 'true' changes in resilience capacities (however you choose to define or measure them). It may well be that seasonal shifts in weather exert a cognitive bias on individuals (perhaps mediated through changes in mood or surrounding environment) as they self-assess throughout the year. Indeed, short-term weather conditions have been recorded as having measurable – though small – effects on subjective evaluations of life satisfaction (Feddersen et al. 2005; Barrington-Leigh & Behzadnejad 2017). It is nevertheless reassuring to observe that controls for time of day, day of the week and mood appear to have little effect on the main findings. Efforts to further unpack the influence of cognitive drivers in self-evaluated resilience scores are sorely needed (Claire et al. 2017).

It is also important to note the SERS approach involves asking the head of household to make a judgement on the capacities of the entire household (typically comprised of multiple individuals). Inevitably, there are likely to be differences in the assessments of one member of the household compared with others from within the same household. Indeed, Fisher et al. (2010) observe this for estimates of household income, where a husband's estimate of their wife's income does not produce statistically reliable results. By selecting survey respondents through randomisation of the main bread-winning couple it is hoped that the effects of such biases can be limited when aggregated with large samples. However, care needs to be taken in noting the potential for individual-level biases to affect household-level evaluations.

Despite these caveats, insights from this paper point to the potential for subjective-evaluations to assist in tracking rapid fluctuations in household resilience. This may be especially relevant in two instances: tracking intra-annual changes in resilience that might not be picked up by objective indicators that are stable over time; and efforts aiming at evaluating the immediate implications of a hazard – such as a flood or heatwave – where quick assessments are needed on the basis of localised knowledge.

Findings point to the need for development actors to pay greater attention to intra-annual changes in resilience. This may mean tailoring resilience-building interventions to changing seasonal needs – with different support provided from one season to the next. Links with seasonally shifting weather patterns can also guide development actors in pointing to potential drivers of change, both across and within seasons. Above all, findings encourage academic and practitioners alike to consider the role and interaction of different contributary factors in shaping intra- and inter-annual levels of resilience: whether momentary, slowly-evolving or stable over time.

Chapter 5

Concluding remarks

As resilience emerges as a key priority on the international development agenda, it is imperative that interventions aimed at building resilience are informed by robust measurement. While conventional objective approaches come with inherent advantages, they are not without weakness. In particular, heavy assumptions around indicator selection, the costliness of data collection, and difficulties in tracking short-term dynamics of resilience often mean that objective measures are of limited practical use to development and humanitarian stakeholders.

In this thesis I have showcased the potential for an alternative and complementary approach to resilience measurement: subjective measures. Below, I highlight key contributions from the four research chapters by relating back to the main aims of the thesis. Namely I sought to: i) establish conceptual boundaries between subjective and objective approaches to resilience measurement; ii) compare outcomes from perception-based tools with those of existing objective measures; and iii) further examine the temporal dynamics of resilience and potential associations with wider environmental factors. Most importantly, I extend the findings from respective chapters to reflect on their implications for our understanding of household resilience. I also consider what results mean for development and humanitarian efforts to promote resilience-building amongst vulnerable communities.

5.1. Clarifying conceptual boundaries

In tackling the first research aim, I began the thesis by laying down the theoretical foundations that distinguish subjective and objective approaches to resilience measurement. Doing so allowed for a broad swathe of existing measurement tools to be classified against clear criteria. In presenting an objectivity-subjectivity continuum, I pointed to four distinct categories of measures. By plotting existing toolkits against the continuum, I revealed that the majority of existing tools fall into a single category: measures that are objectively-defined & objectively-evaluated.

I also pointed to new areas of methodological development – ones that may hold promise for future evaluations. For example, more can be done to explore the potential for subjectively-defined approaches: those capable of factoring local knowledge of resilience attributes and the factors that shape resilience on the ground. More should also be done to develop hybrid measures, where elements of different approaches are combined based on their respective advantages.

Crucially, findings from Chapter 1 help to clarify the conceptual and epistemological boundaries that distinguish objective and subjective measures of resilience. This builds on, and adds to, related theoretical work by Maxwell et al. (2015), Béné et al. (2016b), Clare et al (2017) and Béné et al. (2019). Key contributions can be seen in highlighting the relative strengths and weaknesses of various types of approaches, as well as providing an easy-to-use framework to classify existing measurement tools – serving a field where conflation of subjectivity and objectivity is commonplace (Maxwell et al. 2015). Above all, these findings encourage academics and development practitioners alike to think more carefully about the suitability of different measurement approaches by taking into account respective evidence needs and available resources.

In addition, empirical insights from Chapters 2, 3 and 4 have shed light on the role and relationship of different resilience-related capacities. For example, associations between socio-economic characteristics and different resilience-related capacities (measured using SERS) appear broadly similar. The same traits apply to both the Uganda and Myanmar contexts. Moreover, I revealed how flood exposure exhibits consistent and negative impacts on all resilience-related capacities – including anticipatory, absorptive, adaptive and transformative capacities. These findings have important implications for how resilience is conceptualised and supported. Knowing how different types of shocks influence individual resilience-related capacities can help development and humanitarian actors to tailor their response and recovery activities – a much need avenue for future research.

Indeed, an active debate continues within the academic literature as to the exact make-up and mixture of characteristics constituting the resilience of social systems (see Nelson 2010; Kates & Travis 2012; McEvoy et al. 2013; Béné et al. 2014; Bahadur et al. 2015; Olsson et al. 2015; Aldunce 2015). Yet, insights from Chapters 2, 3 and 4 suggest that SERS modules designed to mimic different resilience frameworks have little impact on measured resilience outcomes. To be clear, this does not render these theoretical debates futile. Far from it. A strong conceptual basis in understanding the components of a resilient system is key to developing effective resilience-building interventions. However, findings from this thesis suggest that different resilience-related capacities may contribute uniformly to a households' overall resilience – at least from the point of subjective-evaluations. They may also exhibit similar associations with key socio-economic drivers.

While these findings provide important quantitative insights to debates on resilience, they do come with caveats. For a start, limitations in question structure and wording used in the SERS approach mean that it is difficult to factor all aspects of a given capacity into a single survey question. This is especially apparent in the case of transformation, whose emphasis within the academic literature has evolved considerably over time (Kates &

Travis 2012; Carr 2019). Future applications of the SERS approach would be well placed to test and compare outcomes from questions worded to match different definitions of resilience-related capacities. This is particularly the case for commonly used capacities like anticipatory, absorptive, adaptive and transformative capacities. I also note that while the effects of flood exposure point in the same direction for all resilience-related capacities in Chapter 3, the strengths of association differ somewhat. It is here that attempts to gather further quantitative evidence on the contributions (and associations) between respective capacities and overall resilience can add considerably to the knowledge base.

5.2. Comparing different approaches to measurement: highlighting the importance of diversity

A second contribution of this thesis has been to compare resilience outcomes between a subjective measure (in the form of SERS) and an objective approach to measurement (using RIMA). In the absence of a large body of quantitative evidence it is important to weigh up outcomes from different types of evaluative measures. Where two all-together different measurement approaches converge, we can draw greater confidence that our underlying assumptions may be accurate. Where they differ, it forces us to take a step back and consider why? What biases may be at play, and do our fundament understandings of resilience need to be reconsidered?

In addressing the second research aim of the thesis, findings from Chapter 1 have shown a positive correlation between SERS and RIMA. That two independent approaches point in a similar direction should provide reassurance to the evaluation community of practice. Moreover, links between resilience and many socio-economic indicators are closely matched. These include factors commonly associated with resilience, such as: asset-wealth; diversification of income sources; livelihood type; distance to key communal assets; as well as access to credit.

Results also provide grounds for further inquest. For a start, the strength of correlation between the two measures is moderate at best ($R^2 = 0.25$). Links with a number of socio-economic variables also differ markedly. In particular, coping strategies, levels of education and exposure to prior shocks each make diverging contributions to the two resilience measures. While more clearly needs to be done to establish the validity of the SERS approach, these findings do pose a challenge to the make-up and design of indicator-based measures likes RIMA. More specifically, it encourages evaluators to reflect carefully on the evidence-based for contributory drivers of resilience. Doing so is especially relevant given that model composition and indicator-selection for many objectively-oriented measures rely heavily on expert judgement (Schipper & Langston 2015; Bahadur & Pichon 2017).

A number of implications are important to consider before firm conclusions can be drawn. Firstly, understanding the basis for different resilience measures is crucial. Each approach will have different theoretical and definitional entry points. This makes it especially difficult to carry out like-for-life comparisons, and is certainly the case for both RIMA (which is primarily focused on food security outcomes) and SERS (which is oriented towards livelihood outcomes). Comparisons between the two also raise important issues of epistemology. Insights from this thesis provide an important reminder that there is no 'gold standard' for resilience measurement (nor may there ever be). Subjective and objective approaches represent alternative attempts at measuring a fundamentally intangible property. The same challenge can be expressed of measures of happiness. Here, subjective interpretations can differ considerably compared with objective ones (OECD 2013), yet neither approach can realistically serve as a 'true' measure of happiness (Kahneman 2000).

While an exact measure of 'true' resilience may not be feasible, it is nonetheless imperative that a range of evidence sources be considered. The resilience measurement community of practice should also be more transparent about the design choices used in developing composite indexes, as well as highlighting their implications for M&E activities. Lifting the veil on assumptions and actions taken in choosing indicators, weights and supportive evidence is an important first step. Efforts should be made to encourage development practitioners to reflect more critically on the choice and suitability of different measurement tools.

Chapter 1 also pointed to the bunching of tools into a one or two categories along the objective-subjective continuum. A real danger therefore exists of collective convergence and herding. That is, given that many resilience measurement tools adopt similar epistemological foundations, statistical methods and rules for indicator selection, it is unsurprising that outcomes and findings largely converge. While adding more tools to the measurement repertoire may give the impression of greater confidence in findings, it can often be misleading in the absence of diverse sources of evidence. Similar traits are well documented in the field of political polling, where herding can lead to over-confidence in election forecasts, suppression of outliers and promotion of group-think (Wring et al. 2018).

In heeding the call for diversity, it is reassuring that SERS exhibits a number of relevant traits. Firstly, resilience scores vary across social groups. If shown to be robust, then it allows for different household traits to be compared and contrasted. It also allows development and humanitarian actors to identify the types of households most in need of external support based on the perceptions of those at risk. That SERS is responsive to external stimuli is similarly encouraging. Not only do resilience scores drop (and eventually rebound) in the aftermath of heavy seasonal flooding, they are associated with changes in seasonality and weather anomalies. Sensitivity to wider social and environmental conditions is an important precondition for robust resilience measurement (FSIN 2014a). It may also point to the utility of using SERS to gauge the extent, duration and heterogeneity of hazard impacts on resilience across different social groups.

Again, care needs to be taken in adequately accounting for the many potential confounders that can affect repeated collection of subjective assessments before scaling up for use in policy and practice. Crucially, more can be done to ground-truth findings from SERS with qualitative and qualitative insights across the various contexts where it is applied.

5.3. Uncovering temporal dynamics of resilience

The third contribution of this thesis has been to shed light on the temporal dynamics of resilience. Levels of resilience do not remain static over time. This property is well established in the academic literature (Keck and Sakdapolrak 2013; Waller 2001). It is also fundamental to development efforts aimed at promoting resilience. Indeed, resilience-building interventions would prove fruitless otherwise. Yet, many resilience-building interventions are designed on the basis that changes in household resilience occur gradually (and linearly) over the course of several years. This sentiment is fuelled, in part, by a tendency for evaluation exercises to be carried out years apart (Schipper and Langston 2015; Wilson and Yarron 2017). Not to mention the 3-5 year project cycles that govern many development and humanitarian interventions. Similarly, much of the focus on temporal dynamics of resilience rests in defining different capacity states: from static resistance to gradual processes of adaptation and transformation (Walker et al. 1981; Kates et al. 2012). Less attention has so far been paid to how levels of individual capacities themselves (i.e. momentary measures of a household's resilience-related capacities) may change over short-term timescales.

There are strong reasons to believe that they do so. Insights from the sustainable livelihoods literature have long pointed to the seasonal nature of livelihood outcomes, poverty and food security (Chambers et al. 1981; Longhurst et al. 1986; Deveroux et al. 2013). In turn, these outcomes play a strong role in determining levels of resilience-related capacities and can be expected to drive short-term changes in household resilience (Aldrich & Meyer 2015). Yet, little in the way of quantitative evidence exists.

By making use of a high-frequency panel dataset, Chapters 3 and 4 have shown how perceived levels of resilience fluctuate over the course of a year. Not only are differences across seasons seen to be statistically significant, changes in self-evaluated scores exhibit significant associations with a range of weather conditions (both with regards to absolute values and anomalies relative to the historical record). I also explored potential drivers for these temporal dynamics. Namely, I introduced three core domains that are likely to influence an individual's self-assessment of household resilience. These include: chronically accessible sources that variably influence resilience; chronically accessible sources that a provide a stable influence on resilience; and temporarily accessible sources that affect individual judgement. It is largely the first trait that is of relevance to our efforts of understanding intra-annual shifts in household resilience – including seasonality and weather. While the second trait is likely of greater relevance in explaining inter-annual shifts. The third trait is of key importance in preventing bias from affecting subjective evaluations – a feature of a number of the robustness tests throughout the Chapters.

The importance of quantitative evidence of seasonal (and intra-seasonal) links with resilience are worth considering. Development and humanitarian actors may consider doing more to tailor resilience-building interventions to changing seasonal needs – similar to seasonal initiatives employed by many social protection programmes (Hagen-Zanker et al. 2017). Findings from Chapter 4 also points to the potential for local weather-related thresholds and tipping points. These insights can help resilience practitioners to better identify time-critical entry points for short-term interventions, such as support to early-warning systems or forecast-based finance initiatives (de Perez et al. 2014). Findings are also relevant to resilience evaluators. M&E efforts conducted at different points in the year risk picking up on seasonal and other intra-annual influences. These can bias efforts to attribute resilience outcomes to the impacts of a given intervention. Greater care should be taken in accounting for these shorter-term confounders in the design of resilience evaluations. This includes: informed choices over suitable measurement tools and indicators; care in deciding the timing and format of data-collection exercises; as well as an emphasis on gathering high-frequency data.

The responsiveness of the SERS module to external shocks and stresses also provides insights into the approach's viability and usefulness. Not only might the approach offer ways to track changes in a households' ability to deal with future threats, it can point to households that fare better or worse. For example, findings from Chapter 3 highlight the difficulties of female-headed households in the aftermath of seasonal flooding in Hpa An. They also suggest that those with greater income diversity had lower resilience scores compared with those indirectly affected by flooding. Interestingly, this not only challenges assumptions in the literature, but contrasts with insights from Chapter 2 in Uganda. Together these results underscore the importance of gathering local information, recognising that the drivers of resilience are likely to be context specific (Adger et al. 2005; Borquez et al. 2017).

Despite promising prospects, care needs to be taken to further assess the robustness of subjective measures likes SERS. Far a start, more can be done to account for the role of cognitive biases (such as priming, psychological adaptation and various environmental cues) in influencing self-reported scores. Here a vast amount of psychological and behavioural science literature offers important insights that can be drawn on further (Connor and Davidson 2003; King and Wand 2006; Tiberius 2006; Lavrakas 2008; Dolan et al. 2011; Mills et al. 2016). Future efforts can also be made to build on and extend the mixed-method approaches used here in ground-truthing self-evaluated scores with qualitative accounts. Above all, further efforts to collect information and insights from across different contexts will be crucial to establishing the robustness of subjectively-evaluated approaches like SERS.

Perhaps the most important opportunity that perception-based measures offer is in complementing conventional objective approaches. In particular, by capitalising on the brevity of the SERS module, this thesis highlights the potential for ICT and mobile technologies to be used in tracking resilience over time. The combination of these two tools has yet to be fully exploited in the context of resilience measurement, and heralds opportunities for low-cost and near-real time evidence gathering. Novelties such as these are especially relevant in post-disaster contexts: environments where it is often unsafe, too expensive or too time-consuming to roll out conventional face-to-face surveys.

Above all, it is hoped that insights from this thesis can spur further methodological innovation. In the case of resilience measurement, it is clear that no single method (or type of evidence) has all the answers. Instead, a plurality of perspectives is needed in gaining a holistic understanding of resilience: a process crucial to safeguarding lives and livelihoods across the Global South.

Appendix A (Chapter 2)

Appendix A Section 1

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

Appendix A Figure 20: An annotated diagram of steps taken in calculating the RIMA-II model. For more details see FAO (2016) and D'Errico et al. (2017).

Appendix A Table 11: Wording used for the hazard-specific variant of the SERS-3A model.

Appendix A Table 12: Loadings from a Principal Components Analysis (PCA) of all nine resilience-related capacities used in the SERS-9A variant.

Appendix A Table 13: Here we present a range of model outputs each with similar setup featuring either 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. Coefficients are unstandardised.

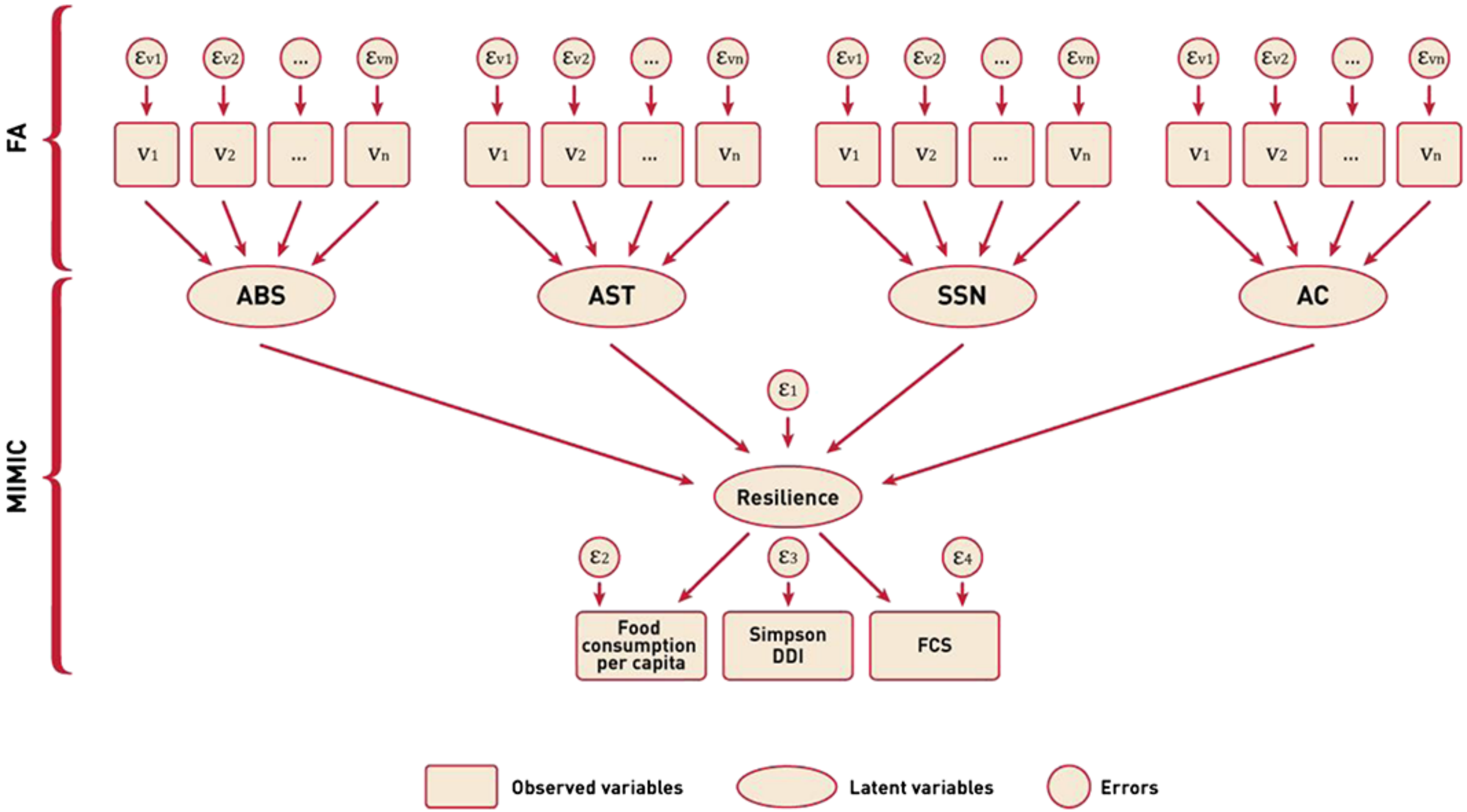
Appendix A Table 14: This features an identical model setup to Appendix A Table 1, comparing a range of regression models. In this case, however, the dependent variables include the original RIMA-II set-up (Models 9-13), with SRES 9C (Models 14-18) featured for ease of comparison. Aside from the choice of dependent variable, model specifications of Models 9-18 are identical to those of Models 1-8 (Appendix A Table 2). Coefficients are unstandardised.

Appendix A Table 15: This table shows model setups that mimic Appendix A Tables 12 and 13. 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 (Appendix A Table 1). Coefficients are unstandardised.

Appendix A Table 16: 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 Béné et al. 2012); and SERS 9C with households that respond with the same answer across each resilience-related capacity removed from the sample. Coefficients are unstandardised.

Appendix A Table 17: A table comparing associations with RIMA and SERS. Models 1-2 are the same set up as the main analysis. Models 3-4 include quadratic functions for all socio-economic drivers.

Figure 20: Composition and structure of the food security format of RIMA-II



Source: D'Errico et al. 2017

Table 11: List of three resilience-related capacity questions used in the 3As

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?

Table 12: Loadings of SERS resilience-related capacities

Capacity	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9
Absorb	0.409	0.128	0.232	0.235	0.257	0.052	0.296	0.111	0.734
Adapt	0.405	0.058	0.239	0.063	0.263	0.239	0.475	0.076	-0.643
Transform	0.369	0.125	0.114	0.121	-0.092	0.566	-0.698	0.060	-0.038
Financial	0.355	0.249	-0.137	0.329	-0.541	-0.220	0.114	-0.572	-0.058
Social	0.208	-0.483	0.650	-0.358	-0.365	-0.186	-0.040	-0.039	0.041
Political	0.092	-0.763	-0.241	0.584	0.059	-0.014	-0.037	0.064	-0.043
Learning	0.358	-0.081	-0.142	-0.270	0.594	-0.387	-0.319	-0.407	-0.045
Anticipatory	0.380	0.153	-0.237	-0.041	-0.195	-0.483	-0.118	0.692	-0.104
Warning	0.287	-0.240	-0.548	-0.524	-0.189	0.393	0.261	-0.034	0.162
Eigenvalues	3.650	1.134	0.878	0.742	0.653	0.647	0.508	0.437	0.350

Notes: Table shows Principal Components Analysis loadings across all nine resilience-related capacities used in the full SERS module

Table 13: Loadings of SERS resilience-related capacities

	RIMA				SERS			
	OLS	OLS (County FE)	OLS (County FE & CSE)	Multi-level (Nested)	OLS	OLS (County FE)	OLS (County FE & CSE)	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 (0.00004)	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 (0.018)	-0.004 (0.029)	-0.017 (0.238)	-0.069 (0.220)	-0.069 (0.148)	-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 (0.146)	0.025 (0.112)
Constant	0.121*** (0.013)	0.108*** (0.018)	0.108*** (0.014)	0.118*** (0.011)	0.499*** (0.037)	0.545*** (0.051)	0.545*** (0.056)	0.518*** (0.041)
Observations	2,146	2,146	2,146	2,146	2,138	2,138	2,138	2,138
Sub-county FE	NO	YES	YES	-	NO	YES	YES	-

Table 14: Summary of model outputs comparing RIMA-II (the original food-security variant) and SERS

	RIMA--II				SERS 9C			
	OLS	OLS (Sub-county FE)	OLS (Sub-county FE & CSE)	Multi-level (Nested)	OLS	OLS (Sub-county FE)	OLS (Sub-county FE & CSE)	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 (0.007)	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 (0.075)	-0.065 (0.038)	-0.017 (0.238)	-0.069 (0.220)	-0.069 (0.148)	-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 (0.146)	0.025 (0.112)
Constant	0.042** (0.014)	0.018 (0.018)	0.018 (0.022)	0.029* (0.014)	0.499*** (0.037)	0.545*** (0.051)	0.545*** (0.056)	0.518*** (0.041)
Observations	2,146	2,146	2,146	2,146	2,138	2,138	2,138	2,138
Sub-county FE	NO	YES	YES	-	NO	YES	YES	-

Table 15: Summary of model outputs comparing RIMA and SRES-PCA variant

	RIMA				SRES-PCA			
	OLS	OLS (Sub-county FE)	OLS (Sub-county FE & CSE)	Multi-level (Nested)	OLS	OLS (Sub-county FE)	OLS (Sub-county FE & CSE)	Multi-level (Nested)
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Wealth index	0.256*** (0.008)	0.243*** (0.008)	0.243*** (0.006)	0.246*** (0.006)	0.128*** (0.021)	0.097*** (0.022)	0.097*** (0.027)	0.108*** (0.021)
Access to agricultural inputs	0.020* (0.008)	0.018* (0.008)	0.018 (0.009)	0.018** (0.006)	0.081*** (0.014)	0.082*** (0.016)	0.082*** (0.017)	0.082*** (0.019)
Access to credit	0.015*** (0.004)	0.019*** (0.004)	0.019*** (0.003)	0.018*** (0.003)	0.002 (0.010)	0.009 (0.010)	0.009 (0.009)	0.007 (0.010)
Crop disease affect (Base=Yes)	0.010*** (0.003)	0.005 (0.003)	0.005 (0.003)	0.006* (0.003)	0.018* (0.009)	0.040*** (0.010)	0.040** (0.013)	0.035*** (0.009)
Number of income sources	0.039*** (0.001)	0.039*** (0.001)	0.039*** (0.001)	0.039*** (0.001)	0.013*** (0.004)	0.013*** (0.004)	0.013** (0.004)	0.013*** (0.004)
Diversity of food intake	-0.0002 (0.0005)	0.001 (0.0005)	0.001 (0.001)	0.0004 (0.0004)	0.009*** (0.001)	0.010*** (0.001)	0.010*** (0.002)	0.009*** (0.001)
log(Distance agri market+1)	-0.002 (0.002)	-0.001 (0.002)	-0.001 (0.001)	-0.001 (0.001)	0.0002 (0.005)	-0.005 (0.005)	-0.005 (0.007)	-0.003 (0.005)
Highest female education	0.005*** (0.0003)	0.005*** (0.0003)	0.005*** (0.0004)	0.005*** (0.0003)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Annual food consumption	0.0001* (0.00004)	0.00003 (0.00004)	0.00003 (0.00004)	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)	0.00004 (0.0002)	-0.00004 (0.0002)	-0.00004 (0.0002)	-0.00003 (0.0002)
Age of household head	0.019*** (0.001)	0.022*** (0.001)	0.022*** (0.001)	0.021*** (0.001)	-0.008** (0.003)	-0.009** (0.003)	-0.009* (0.004)	-0.008** (0.003)
Education of household head	0.006*** (0.0004)	0.005*** (0.0004)	0.005*** (0.0004)	0.006*** (0.0003)	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)
Number of children	-0.005*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.004 (0.002)	-0.004 (0.002)	-0.004 (0.003)	-0.004 (0.002)
Flood affect (Base=Yes)	-0.006 (0.004)	-0.011* (0.005)	-0.011* (0.005)	-0.010* (0.005)	-0.019 (0.013)	-0.021 (0.015)	-0.021 (0.020)	-0.020 (0.015)
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)	-0.019*** (0.005)	-0.019* (0.008)	-0.018*** (0.005)
log(Distance hospital+1)	-0.005*** (0.001)	-0.004*** (0.001)	-0.004** (0.002)	-0.005*** (0.001)	-0.014*** (0.004)	-0.012** (0.004)	-0.012* (0.005)	-0.013** (0.004)
Coping Strategies Index (inv)	0.209*** (0.008)	0.205*** (0.008)	0.205*** (0.010)	0.206*** (0.006)	-0.005 (0.023)	-0.014 (0.023)	-0.014 (0.031)	-0.012 (0.019)
Farming livelihood (Base=Agro-pastoral)	-0.021*** (0.002)	-0.017*** (0.002)	-0.017*** (0.002)	-0.018*** (0.002)	-0.032*** (0.008)	-0.031*** (0.008)	-0.031*** (0.009)	-0.031*** (0.008)
Illness affect (Base=Yes)	-0.005 (0.003)	-0.005 (0.003)	-0.005 (0.003)	-0.005 (0.003)	-0.033** (0.011)	-0.027* (0.011)	-0.027* (0.012)	-0.028** (0.011)
Drought affect (Base=Yes)	0.005 (0.004)	0.009* (0.004)	0.009 (0.004)	0.008* (0.004)	-0.053*** (0.014)	-0.040** (0.015)	-0.040* (0.020)	-0.044*** (0.013)
Gender household head (Base=Female)	-0.002 (0.027)	-0.004 (0.028)	-0.004 (0.018)	-0.004 (0.029)	0.052 (0.220)	0.020 (0.196)	0.020 (0.132)	0.033 (0.095)
Relationship status (Base=Divorced/separate)	-0.012 (0.027)	-0.011 (0.028)	-0.011 (0.017)	-0.011 (0.029)	-0.066 (0.220)	-0.040 (0.196)	-0.040 (0.131)	-0.051 (0.095)
Constant	0.121*** (0.013)	0.108*** (0.018)	0.108*** (0.014)	0.118*** (0.011)	0.298*** (0.032)	0.283*** (0.042)	0.283*** (0.043)	0.308*** (0.035)
Observations	2,146	2,146	2,146	2,146	2,138	2,138	2,138	2,138
Sub-county FE	NO	YES	YES	-	NO	YES	YES	-

Table 16: Comparison of variants of the SRES approach

	SRES-9C	SRES-3A	SRES-AAT	SRES-9C (excluding same responses)
	(25)	(26)	(27)	(28)
Wealth index	0.107*** (0.030)	0.134*** (0.028)	0.126*** (0.027)	0.099*** (0.031)
Access to agricultural inputs	0.083*** (0.021)	0.084*** (0.026)	0.102*** (0.026)	0.071*** (0.019)
Access to credit	0.025** (0.012)	0.015 (0.013)	0.029* (0.016)	0.029** (0.013)
Crop disease affect (Base=Yes)	0.030** (0.014)	0.019 (0.016)	0.010 (0.015)	0.031** (0.015)
Number of income sources	0.012** (0.005)	0.013** (0.005)	0.015*** (0.006)	0.010** (0.005)
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* (0.0002)
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 (0.025)	-0.006 (0.031)
log(Distance livestock market+1)	-0.022*** (0.008)	-0.019** (0.008)	-0.018** (0.009)	-0.023*** (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 (0.041)	-0.041 (0.042)	-0.052 (0.039)
Farming livelihood (Base=Agro-pastoral)	-0.039*** (0.011)	-0.046*** (0.014)	-0.053*** (0.013)	-0.034*** (0.012)
Illness affect (Base=Yes)	-0.043*** (0.016)	-0.025 (0.017)	-0.028 (0.018)	-0.042** (0.017)
Drought affect (Base=Yes)	-0.040 (0.025)	-0.041* (0.023)	-0.055** (0.026)	-0.041* (0.025)
Gender household head (Base=Female)	-0.069 (0.148)	-0.015 (0.173)	-0.015 (0.150)	-0.077 (0.154)
Relationship status (Base=Divorced/separate)	0.043 (0.146)	-0.009 (0.172)	-0.021 (0.149)	0.057 (0.152)
Observations	2,138	2,142	2,142	2,076
Sub-county FE	NO	YES	YES	YES

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

Table 17: Inclusion of quadratic terms for socio-economic drivers

	RIMA (1)	SERS (2)	RIMA (3)	SERS (4)
Wealth index	0.243*** (0.006)	0.107*** (0.030)	0.228*** (0.017)	-0.033 (0.069)
Wealth index ^2			0.019 (0.026)	0.243** (0.088)
Access to agricultural inputs	0.018 (0.009)	0.083*** (0.021)	0.014 (0.008)	0.061** (0.023)
Access to credit	0.019*** (0.003)	0.025* (0.012)	0.019*** (0.003)	0.029* (0.013)
Crop disease affect (Base=Yes)	0.005 (0.003)	0.030* (0.014)	0.004 (0.003)	0.033* (0.014)
Number of income sources	0.039*** (0.001)	0.012* (0.005)	0.038*** (0.004)	0.013 (0.012)
Number of income sources ^2			0.0002 (0.001)	-0.001 (0.002)
Diversity of food intake	0.001 (0.001)	0.011*** (0.002)	-0.001 (0.001)	0.004 (0.007)
Diversity of food intake ^2			0.00005 (0.0001)	0.0004 (0.0003)
log(Distance agri market+1)	-0.001 (0.001)	-0.001 (0.007)	-0.027** (0.010)	-0.098** (0.031)
log(Distance agri market+1) ^2			0.004** (0.001)	0.013** (0.004)
Highest female education (yrs)	0.005*** (0.0004)	0.002 (0.001)	0.004*** (0.001)	0.006 (0.004)
Highest female education (yrs) ^2			0.0001 (0.0001)	-0.0004 (0.0003)
Annual food consumption	0.00003 (0.00004)	0.0003 (0.0001)	0.0001 (0.0001)	0.0002 (0.0003)
Annual food consumption ^2			-0.00000 (0.00000)	0.00000 (0.00000)
Crop diversification	0.0001 (0.0001)	-0.0001 (0.0003)	0.001** (0.0004)	-0.0003 (0.002)
Crop diversification ^2			-0.00001** (0.00000)	0.00000 (0.00001)
Age of household head	0.022*** (0.001)	-0.007 (0.005)	0.031*** (0.002)	0.039** (0.012)
Age of household head ^2			-0.001*** (0.0003)	-0.007*** (0.002)
Education of household head (yrs)	0.005*** (0.0004)	-0.003* (0.001)	0.006*** (0.001)	-0.003 (0.003)
Education of household head (yrs) ^2			-0.00004 (0.0001)	0.0001 (0.0003)
Number of children	-0.006*** (0.001)	-0.005 (0.003)	-0.013*** (0.002)	-0.013* (0.006)
Number of children ^2			0.001** (0.0003)	0.001 (0.001)
Flood affect (Base=Yes)	-0.011* (0.005)	-0.006 (0.029)	-0.008 (0.004)	-0.006 (0.027)
log(Distance livestock market+1)	-0.004 (0.002)	-0.022** (0.008)	0.004 (0.010)	0.064* (0.026)
log(Distance livestock market+1) ^2			-0.001 (0.001)	-0.011** (0.003)
log(Distance hospital+1)	-0.004** (0.002)	-0.016* (0.007)	-0.008 (0.006)	-0.011 (0.026)
log(Distance hospital+1) ^2			0.001 (0.001)	-0.0004 (0.004)
Coping Strategies Index (inv)	0.205*** (0.010)	-0.045 (0.037)	0.341*** (0.047)	-0.085 (0.186)
Coping Strategies Index (inv) ^2			-0.141*** (0.042)	0.030 (0.181)
Farming livelihood (Base=Agro-pastoral)	-0.017*** (0.002)	-0.039*** (0.011)	-0.017*** (0.002)	-0.038*** (0.011)
Illness affect (Base=Yes)	-0.005 (0.003)	-0.043** (0.016)	-0.003 (0.003)	-0.040* (0.016)
Drought affect (Base=Yes)	0.009 (0.004)	-0.040 (0.025)	0.007 (0.004)	-0.046* (0.023)
Gender household head (Base=Female)	-0.004 (0.018)	-0.069 (0.148)	0.005 (0.022)	-0.090 (0.168)
Relationship status (Base=Divorced/separate)	-0.011 (0.017)	0.043 (0.146)	-0.021 (0.023)	0.064 (0.166)
Constant	0.108*** (0.014)	0.545*** (0.056)	0.111*** (0.027)	0.544*** (0.077)
Observations	2,146	2,138	2,146	2,138
Adjusted R^2	0.852	0.177	0.858	0.194
Residual Std. Error	0.049 (df = 2074)	0.188 (df = 2066)	0.048 (df = 2061)	0.186 (df = 2053)

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

Appendix B (Chapter 3)

Table 18: List of resilience-related capacity questions used in the numerous variants of the Subjectively-Evaluated Resilience Score

Preamble: 'I am going to read out a series of statements. Please tell me the extent to which you agree or disagree with them.' [Read out each statement and ask] 'Would you say that you strongly agree, agree, disagree, strongly disagree or neither agree nor disagree that:'

Resilience-related capacity	Survey question
Absorptive capacity	Your household can bounce back from any challenge that life throws at it
Adaptive capacity	If threats to your household became more frequent and intense, you would still find a way to get by
Anticipatory capacity	Your household is fully prepared for any future disasters that may occur in your area
Transformative capacity	During times of hardship, your household can change its primary income or source of livelihood if needed
Financial capital	During times of hardship, your household can access the financial support you need
Social capital	Your household can rely on the support of family and friends when you need help
Political capital	Your household can rely on support from politicians and government when you need help
Learning	Your household has learned important lessons from past hardships that will help you better prepare for future threats
Early warning	Your household receives useful information warning you about future risks in advance

Notes: The full SERS model uses all nine resilience-capacity questions, named the 9-C model. For the purposes of this study, we use the shortened 3A variant of the SERS model with uses Absorptive, Adaptive and Anticipatory capacities. Jones and D'Errico (2019) also use another variant, named AAT, comprising of Adaptive, Absorptive and Transformative capacities.

Figure 21: Key socio-economic characteristics of survey respondents

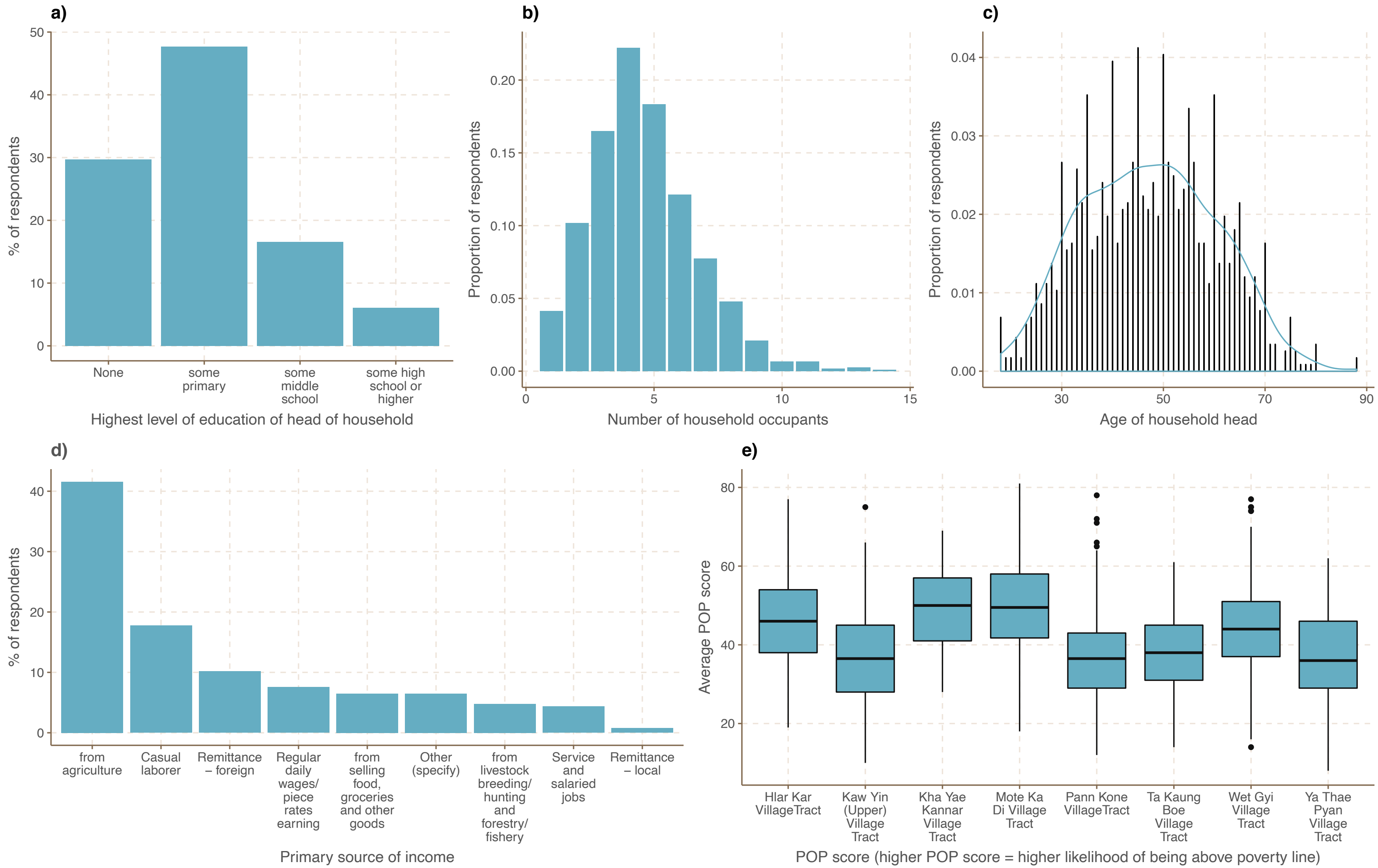
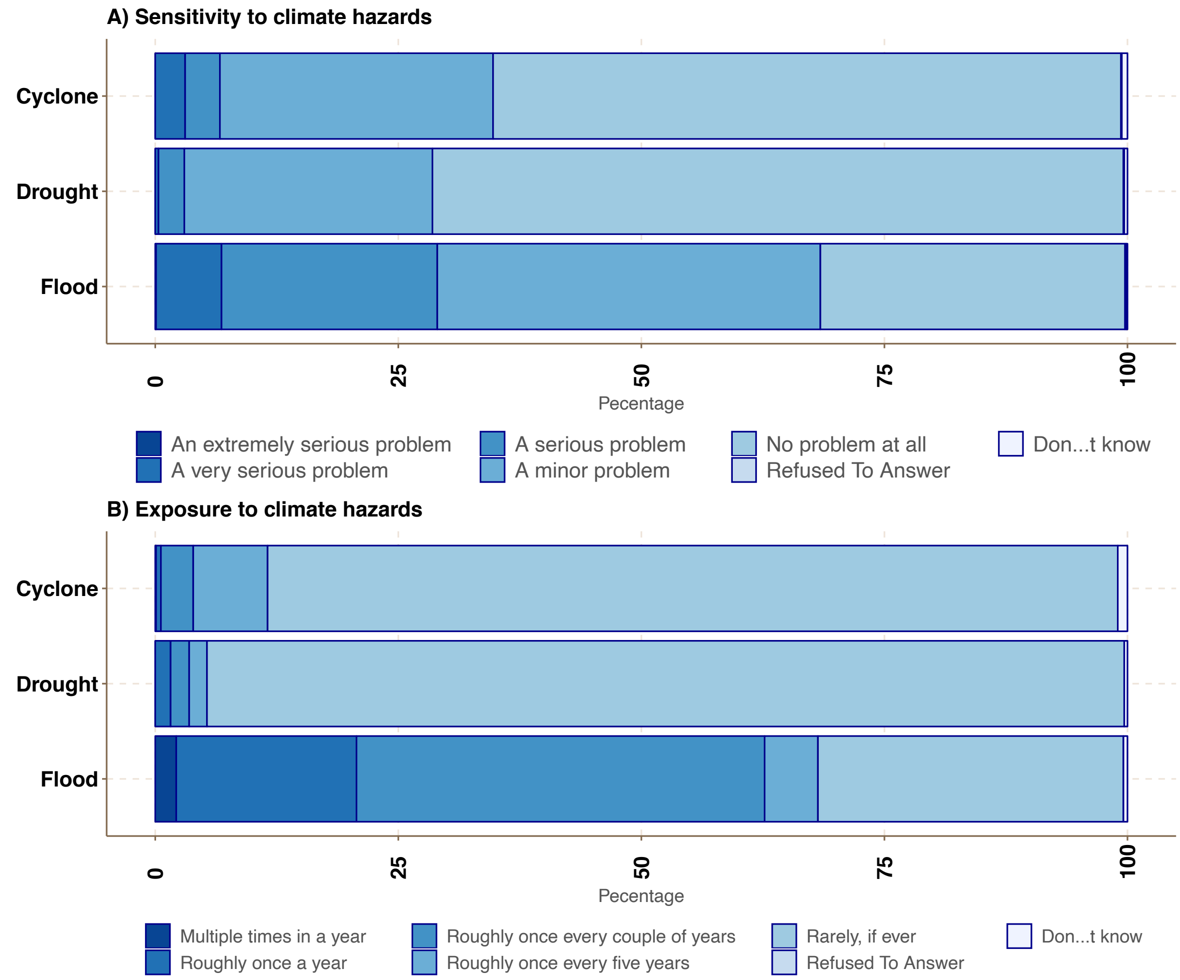


Figure 22: Risk perception: self-reported sensitivity and exposure to cyclones, droughts and floods in Hpa An



Note: For sensitivity respondents were asked, 'Please rate the following extreme weather events in accordance with how serious a problem they have been to your household's ability to survive and thrive in the past 5 years'; For exposure respondents were asked, 'On average, how often would you say your household is affected by the following extreme weather events?'

Appendix B Section 1

What factors are associated resilience during the baseline survey?

One important aspect of the survey is understanding baseline levels of resilience. As highlighted in Table 6 (main text) mean subjectively-evaluated resilience score across all households is 0.54 (SD=0.18). Yet, this is somewhat uninformative without comparing across households. To do so we regress baseline SERS scores, $Resilience_{hv}$ against a number of key social-economic and demographic variables, $Socio_{hv}$. In addition, $Capacity_{hv}$ is a list of factors commonly associated with household resilience and $\xi_{hv}$are village-level fixed effects.

$$Resilence_{hv} = \beta_0 + \beta_1 Socio_{hv} + \beta_2 Capacity_{hv} + \xi_v + e_{hv} \qquad 1)$$

Results from the model show that baseline resilience scores are positively associated with a number of socioeconomic traits, including education of the household head, lower likelihood of poverty, gender of household head and number of household occupants. Age of household head appears to be negatively associated with resilience, as does the gender of respondent. As respondent gender (1=Female) is randomised this potentially signals a difference in the way that males and females perceive their respective households – though note the low-level of statistical significance ($p<0.1$). With regards to factors commonly associated with resilience, higher life satisfaction is strongly significant (those with higher life satisfaction have higher resilience scores). Lastly, households that are further away from the main river (the Thanlwin) also appear to have lower resilience scores when controlling for all other factors (note here that the SERS resilience module is not specific to flood resilience).

Table 19: Factors associated with subjectively-evaluated resilience for the Hpa-An baseline survey

	(1)	(2)
Dummy for education of household head (0=None; 1=Some schooling)	0.05*** (0.01)	0.05*** (0.01)
Age of respondent	-0.001*** (0.0004)	-0.001*** (0.0004)
POP poverty score (high score = higher likelihood of not in poverty)	0.002*** (0.001)	0.002*** (0.001)
Mean number of HH occupants	0.01*** (0.002)	0.01*** (0.002)
Dummy for farmer as primary source of income (1=Farmer)	-0.03** (0.01)	-0.03* (0.01)
Dummy for remittance as primary source of income (1=Remittance)	0.02 (0.01)	0.02** (0.01)
Gender of HH head (1=Female)	0.03*** (0.01)	0.03** (0.01)
Respondent gender (1=Female)	-0.02* (0.01)	-0.02** (0.01)
Risk perception: dummy for flood sensitivity (1=Very serious problem)		0.01 (0.01)
Risk perception: dummy for flood exposure (1=Once a year or more)		0.001 (0.02)
Life satisfaction		0.03*** (0.01)
Number of sources of livelihood		0.001 (0.01)
Distance to the river (log+1)		-0.02* (0.01)
Distance to nearest road (log+1)		-0.01 (0.01)
Observations	1,072	1,052
Adjusted R2	0.17	0.19
Residual Std. Error	0.16 (df = 1056)	0.16 (df = 1030)

*Note: All models include Village fixed effects. Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 200 replications and shown in parentheses, *p<0.1** p<0.05p***p<0.01*

For details on question wording see Appendix B Table 18

Table 20: Questions and response items for variables of interest in the Hpa An survey

Variable	Question	Response items	Notes
Flood impact	Since we last called you on [DATE], has your household been affected by any significant shocks or events that have had a large negative effect on your household's way of life?	Yes No Don't know	Respondents that answer as affected are asked a follow up question: 'What is the primary cause of this shock or event?' (with Flood one of the options available). Responses are then collapsed into binary variables, including: Floods, Landslides, Irregular/Unseasonal rain, Strong wind/tornado, Disease destroying crop, Sudden loss livestock, Social unrest, Fall in price of a good that the HH sells, Increase in price of food or other essential item, Medical emergency, Serious accident at work or home, Death of the income generator, Sudden loss of productive assets, Loss of job.
Risk perception: flood sensitivity	Would you say that flooding poses an extremely serious problem, a very serious problem, a serious problem, a minor problem or no problem at all?	An extremely serious problem A very serious problem A serious problem A minor problem No problem at all Refused to Answer Don't know	Premable: "I would like to ask you about what would happen if a flood were to affect your household in the near future. By severe flood I mean one that is likely to negatively affect your household, or harm your dwelling, fields, or resources. Please rate how serious a problem flooding has been to your household's ability to survive and thrive in the past 5 years." Question asked during the baseline of the survey. Responses then collapsed into binary variable (extremely serious/very serious/serious=serious problem; minor/no problem=not serious problem)
Risk perception: flood exposure	On average, how often would you say your household is affected by flooding?	Multiple times in a year Roughly once a year Roughly once every couple of years Roughly once every five years Rarely, if ever Refused to Answer Don't know	Question asked during the baseline of the survey. Category collapsed into binary variable (multiple times/roughly one a year=once a year or more; every couple/once every five/rarely=less than once a year)
Life satisfaction	All things considered, how satisfied are you with your life as a whole these days?	Very dissatisfied with life Dissatisfied with life Neither satisfied nor dissatisfied Satisfied with life Very satisfied with life Refused to Answer Don't know	Question asked during the baseline of the survey. Treated as a cardinal variable.
Self-evaluation of local environmental change	Has the health of the natural environment around you changed in recent years?	It is improving considerably It is improving slightly It is not changing It is worsening slightly It is worsening considerably	Question asked during Wave 6 of the survey. Treated as a cardinal variable and time invariant.

Table continued: Questions and response items for variables of interest in the Hpa An survey

Variable	Question	Response items	Notes
Coping mechanisms	'What coping mechanisms has your household employed in responding to the shock event since its occurrence? Please list up to three'	1. Household members migrated 2. Engaged in spiritual efforts - prayer, sacrifices, divine consultations 3. Obtained credit 4. Ask for remittances from those outside the household 5. Received help from NGO/religious institution 6. Received help from government 7. Sought new forms of livelihood or work 8. Rely on own saving 9. Changed eating patterns (relied on less preferred food): options, reduced proportion or number of meals/day, or household members skipped days of eating, etc)" 10. Received help from relatives/friends 11. Sent children to live elsewhere 12. Reduced expenditures on household good 13. Took child out of school 14. Sold agricultural assets or goods 15. Did not do anything	Question only asked to households that self-report as affected by a disaster. Responses are post-coded afterward. Responses are then formed into a binary variables, with a primary coping mechanism constituting a response to any recovery mechanism (each households was able to choose up to three).
Primary livelihood	'What is main source of income for this household?'	1. From agriculture 2. from livestock breeding/ 3. hunting and forestry/ fishery 4. from selling food, groceries 5. and other goods 6. Income from services 7. Salary 8. Regular daily wages/ piece 9. rates earning 10. Casual laborer 11. Remittance - local 12. Remittance - foreign 13. Other (specify)	Question asked during the baseline survey. Responses to formed into binary variables used in the regression analyses
Access to climate information during last flood	Do you have access to weather forecasts and climate information?	Yes No	Question asked to all respondents in Wave 5 of the survey, irrespective of flooding
Early warning information	Did you receive information warning your household about the flood in advance?	Yes No	Question only asked to respondents that self-reported as directly affected by a flood since the last round of the survey, and asked in relation to the flood event in question

Appendix B Section 2:

A key decision made early on in the analysis is use of a reduced form of the SERS model; we opt for a version with three resilience-capacity questions rather than the full model with nine questions. To test the implications of this decision we run side-by-side analyses of different variants of the SERS module for the baseline survey in Appendix B Table 21 (set-ups are similar to Appendix B Table 19). Model 1) shows results from the 3A variant of the SERS module used in the main analysis, Models 2) and 3) use the 9C (all 9 questions) and AAT (including questions related to adaptive, anticipatory and transformative capacities) variants respectively[21]. Though statistical significance varies across some variables, signs and magnitudes of effect sizes are broadly similar across all three, implying that results are somewhat consistent across different characterisations of resilience. We also re-rerun the analysis with a variant of the SERS that weights based on a principal component analysis (rather than the standard methods of equal mean weighting) and see no large qualitative differences in key trends.

Turning to the validity of resilience-over-time scores, a number of selection choices should be considered. The first is whether to include data from the face-to-face survey alongside the wider phone panel. This is particularly important given well-documented differences in subjective scores between the two modes of administration (Dolan & Kavetsos 2016). The second, is how to deal with missing values when calculating a resilience-over-time score (as any such values need to be interpolated). In order to test these formally we replicate Equation 4 with three different specifications. In Appendix B Table 22, Model 1) is the same set-up as in the main analysis and removes only households that have three or more missing resilience scores, or a missing value for either the starting (baseline) or finishing waves (wave 7). Model 2) excludes any household that has a missing value for a resilience score across any wave of the survey. While Model 3) excludes resilience scores from the face-to-face survey and starts calculating the area under the curve as of the first phone survey. Given that Model 3) includes one fewer survey than the rest, we calculate the resilience-over-time score as the area under the curve for 6 subsequent waves (rather than 7 in the main analysis). As is clear from Appendix B Table 22, though small differences exist, results appear to be similar in sign and significance across most variables of interest for the three specifications.

In rare cases, the original respondent was unable to pick up the phone and another member of the household carried out the survey in their place. Given the potential for confounding individual influences we rerun the main difference in difference analyses with a subset of the dataset that excludes values obtained from non-original respondents (Appendix B Table 23). Again, we see few differences in the main outcome.

Another crucial aspect to consider is how many time periods to include in calculating the resilience-over-time scores. While use of data from a larger number of waves provides more nuanced information on a household's recovery, it also risks being influenced by other external factors (like wider socio-economic of environmental threats) that make it

[21] The AAT variant is meant to mimic the framework proposed by Béné et al. 2012. For full details of the questions and methods used in the variants see Jones (2018a)

difficult to make comparisons across groups. The choice of all 7 waves of phone survey data in calculating the AUC is borne of the desire to use all information available. However, in Appendix B Table 24 we compare multiple resilience-over-time scores, starting with the use of just three waves and adding an additional wave each time, up to a total of 7 waves. We also plot distributions of resilience scores in Appendix B Figure 24. While small differences are apparent, signs and levels of significance are largely consistent.

We recognise that assessments of perceived levels of resilience are subjective in nature. Unfortunately, limitations in mobile surveys (typically restricted to 10-12 mins in duration) do not lend themselves to applying 'objective' measures of resilience such as the RIMA toolkit (FAO 2016[22]). However, we can make a useful comparison with changes in self-reported levels of monthly income – often considered a proxy for a household's economic resilience (Sturgess 2016) – collected during two waves of the survey (one prior to the floods and the other a number of months after). In Appendix B Table 25 we compare self-reported incomes between the baseline and Wave 5 of the survey using a difference-in-differences set-up similar to the main analysis. In doing so we see no statistically significant differences between direct and indirectly affected households. While this may point to differences in definitional outcomes of resilience, we refrain from drawing firm conclusions as it is far from a like-for-like comparison. Well-documented weaknesses in self-reported income measures (Fukuoka, et. al 2007) also mean that consumption-based measures (such as the POP poverty score used in the main analysis) are far preferred. Still, we believe that dedicated future analyses comparing subjective resilience and other proxies for resilience will have considerable merit.

Lastly, subjective assessments may be prone to different societal and environmental cues (Metcalfe et al. 2016). As such, we re-run the main difference-in-differences set-up for resilience scores with the inclusion of controls for day-of-the-week of the interview, time-of-the-day of the interview and weather on the day of interview (including average temperature, precipitation, dew point). Reassuringly, Table 26 show few differences in the paper's main outcome.

[22] For more on direction comparisons of objective and subjectively-evaluated resilience see Jones and D'Errico (2019).

Table 21: Comparison of associations with resilience using different versions of the SERS module

	SERS-3A	SERS-9C	SERS-AAT
	(1)	(2)	(3)
Dummy for education of household head (0=None; 1=Some schooling)	0.05*** (0.01)	0.14*** (0.04)	0.21*** (0.07)
Age of respondent	-0.001** (0.0003)	-0.003*** (0.001)	-0.01*** (0.002)
POP poverty score (high score = higher likelihood of not in poverty)	0.002*** (0.0005)	0.003*** (0.001)	0.002 (0.002)
Mean number of HH occupants	0.01*** (0.002)	0.03*** (0.004)	0.02** (0.01)
Dummy for farmer as primary source of income (1=Farmer)	-0.03* (0.01)	-0.08** (0.04)	-0.11*** (0.04)
Dummy for remittance as primary source of income (1=Remittance)	0.02** (0.01)	0.07*** (0.03)	0.07 (0.05)
Gender of HH head (1=Female)	0.02*** (0.01)	0.08*** (0.03)	0.08* (0.05)
Respondent gender (1=Female)	-0.02** (0.01)	-0.06** (0.03)	-0.13*** (0.05)
Risk perception: dummy for flood sensitivity (1=Very serious problem)	0.01 (0.01)	0.01 (0.01)	-0.01 (0.04)
Risk perception: dummy for flood exposure (1=Once a year or more)	0.001 (0.02)	0.03 (0.05)	0.09 (0.06)
Life satisfaction (higher score=higher life satisfaction	0.03*** (0.01)	0.04*** (0.01)	0.12*** (0.02)
Number of sources of livelihood	0.0002 (0.01)	-0.002 (0.01)	-0.01 (0.02)
Distance to the river (Log+1)	-0.02* (0.01)	-0.04 (0.03)	-0.02 (0.02)
Distance to nearest road (Log+1)	-0.01 (0.01)	-0.002 (0.01)	-0.01 (0.03)
Observations	1,057	1,057	1,057
Adjusted R^2	0.18	0.20	0.21
Residual Std. Error (df = 1034)	0.16	0.41	0.69

*Note: All models include Village-level fixed effects. Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 200 replications and shown in parentheses, *p<0.1** p<0.05p***p*

Table 22: Associations with resilience-over-time for different methods of dealing with missing values

	Fewer than 3 missing responses (phone & baseline) (1)	No missing responses across all waves (phone and baseline) (2)	Phone only (3)
Dummy for education of household head (0=None; 1=Some schooling)	0.17 (2.45)	-0.71 (2.12)	0.65 (2.18)
Age of respondent	0.22*** (0.04)	0.22*** (0.04)	0.19*** (0.03)
POP poverty score (high score = higher likelihood of not in poverty)	0.09 (0.06)	0.12** (0.05)	0.11* (0.06)
Mean number of HH occupants	0.82 (0.58)	1.09* (0.61)	0.87 (0.60)
Dummy for farmer as primary source of income (1=Farmer)	5.53*** (1.96)	4.83** (1.94)	5.07*** (1.74)
Dummy for remittance as primary source of income (1=Remittance)	-1.30 (1.33)	-1.79 (1.11)	-0.97 (1.22)
Gender of HH head (1=Female)	-2.87 (2.71)	-3.35 (2.84)	-2.11 (2.82)
Respondent gender (1=Female)	-1.48 (1.27)	-0.69 (1.88)	-1.39 (1.03)
Risk perception: dummy for flood sensitivity (1=Very serious problem)	-3.91 (2.49)	-4.45* (2.70)	-3.63 (2.67)
Risk perception: dummy for flood exposure (1=Once a year or more)	-0.66 (2.04)	-0.43 (2.55)	-0.91 (2.12)
Life satisfaction	4.01*** (1.14)	3.84*** (1.30)	3.34*** (1.27)
Number of sources of livelihood	-1.39 (0.92)	-0.54 (0.99)	-1.42 (1.00)
Distance to the river (log+1)	-1.52** (0.67)	-0.76 (0.92)	-1.61*** (0.60)
Distance to nearest road (log+1)	-5.61*** (1.42)	-4.19** (1.94)	-4.35*** (1.35)
Baseline control	YES	YES	YES
Village fixed effects	YES	YES	YES
Observations	1,040	925	1,009
Adjusted R2	0.24	0.26	0.18
Residual Std. Error	26.25 (df = 1017)	25.83 (df = 902)	24.41 (df = 986)

*Note: To ensure comparability across the models, the AUC resilience-over-time scores are calculated up to Wave 6 for models 1 and 2 (rather than Wave 7 in the main analyses) owing to the fact that the phone-only variant in Model 3 has one fewer wave (i.e. no baseline). Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 200 replications and shown in parentheses, *p<0.1** p<0.05p***p<0.01*

Figure 23: Histogram of Resilience-over-time scores for difference variants amongst the entire Hpa An sample

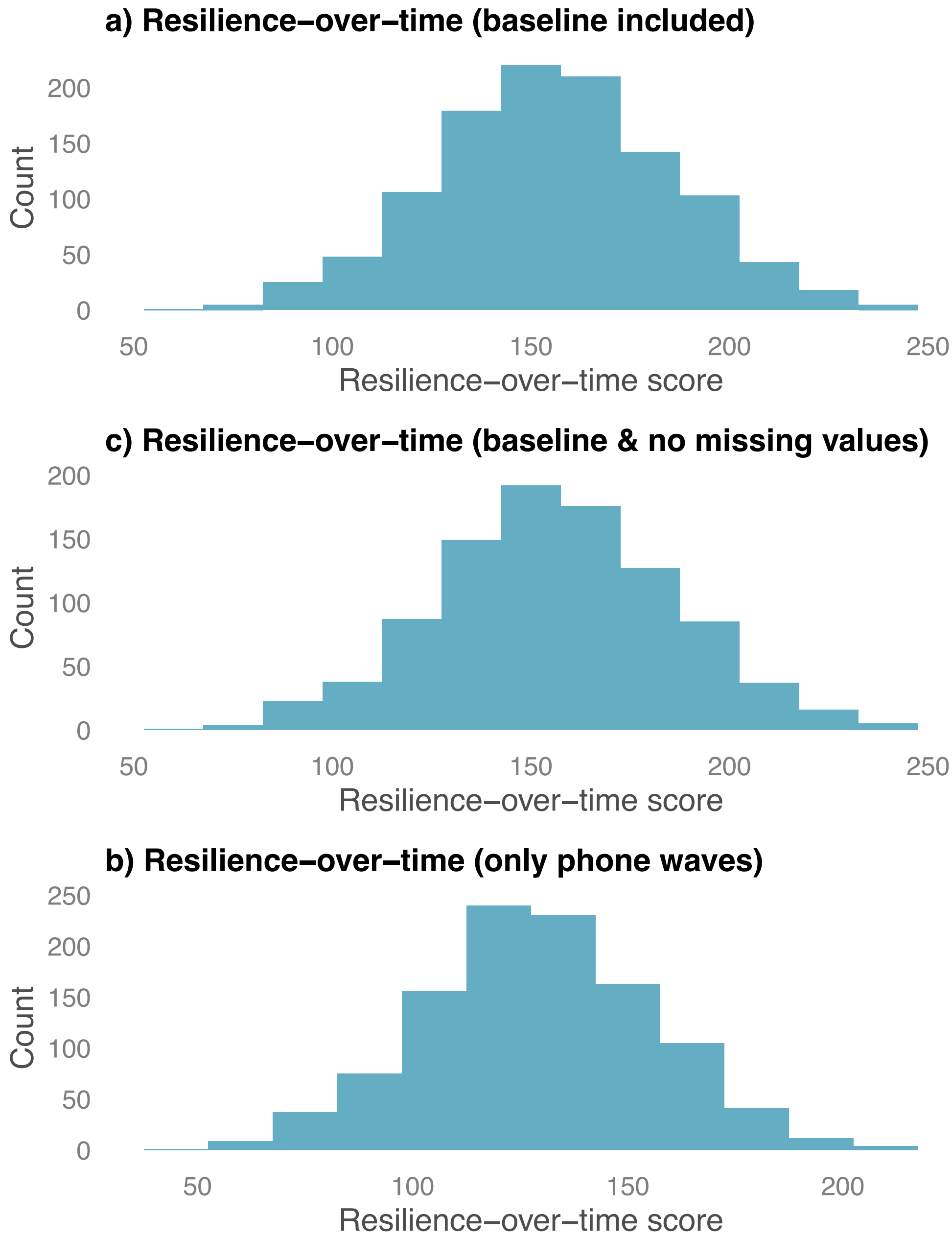


Table 23: Difference in differences for sample of same respondents only

	Unweighted	IPTW
f · post (Difference in Differences)	-0.09*** (0.02)	-0.07*** (0.03)
Household fixed effects	YES	YES
Wave fixed effects	YES	YES
Observations	7,520	6, 267
Adjusted R-Squared	0.31	0.21
Residual Std. Error	0.17 (df = 6572)	0. 17 (df = 6249)

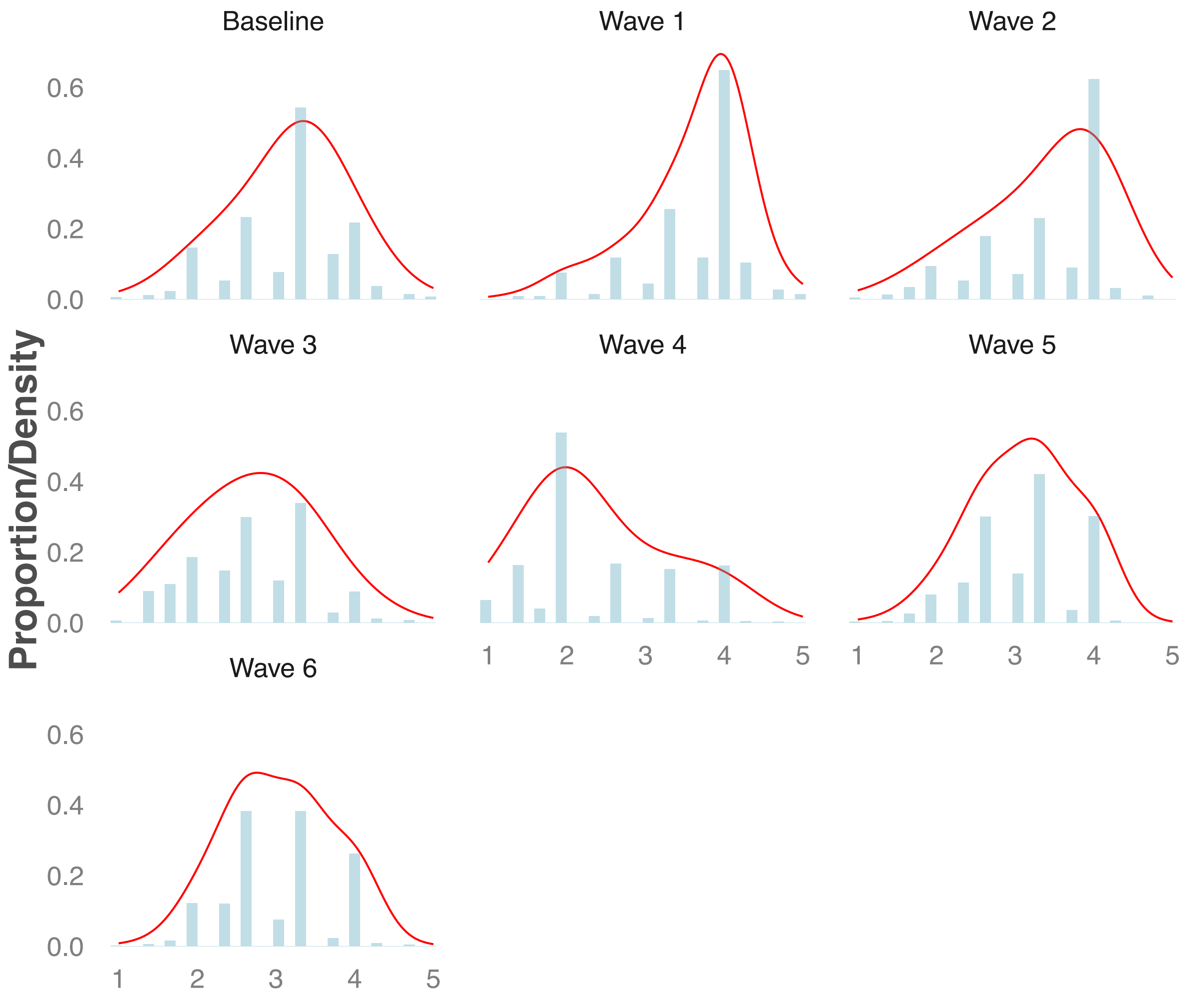
*Note: Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 200 replications and shown in parentheses, *p<0.1** p<0.05p***p<0.01*

Table 24: Differences in associations with Resilience-over-time for different end-points of the AUC

	3 waves	4 waves	5 waves	6 waves	7 waves
Dummy for flood impact (0=Indirect;1=Direct)	-6.58*** (1.10)	-5.13* (2.87)	-5.35* (2.76)	-6.28* (3.43)	-7.87* (4.05)
Baseline resilience score	34.43*** (3.12)	43.25*** (3.29)	48.35*** (3.30)	51.73*** (4.00)	54.10*** (4.17)
Dummy for education of household head (0=None; 1=Some schooling)	-1.93* (1.10)	-2.20 (1.89)	-0.89 (2.22)	-1.35 (2.50)	0.29 (2.76)
Age of respondent	0.13*** (0.03)	0.17*** (0.03)	0.18*** (0.04)	0.20*** (0.04)	0.24*** (0.05)
POP poverty score (high score = higher likelihood of not in poverty)	0.04 (0.04)	0.07 (0.06)	0.08 (0.05)	0.13** (0.06)	0.13** (0.05)
Mean number of HH occupants	0.48* (0.27)	0.65* (0.39)	0.66 (0.49)	0.84 (0.58)	1.07* (0.57)
Dummy for farmer as primary source of income (1=Farmer)	2.48** (1.11)	2.65* (1.60)	3.76** (1.90)	4.92*** (1.87)	4.66** (1.81)
Dummy for remittance as primary source of income (1=Remittance)	-1.45*** (0.51)	-1.72** (0.85)	-1.06 (1.00)	-1.36* (0.72)	-1.13 (0.93)
Gender of HH head (1=Female)	-2.07** (1.01)	-3.65** (1.44)	-3.49 (2.18)	-3.30 (2.59)	-4.30* (2.60)
Respondent gender (1=Female)	0.43 (0.67)	0.25 (0.88)	-1.33 (1.17)	-1.72 (1.35)	-1.71 (1.25)
Baseline resilience FE	YES	YES	YES	YES	YES
Village-level FE	YES	YES	YES	YES	YES
Observations	1,064	990	1,065	1,056	1,072
Adjusted R^2	0.23	0.22	0.21	0.22	0.23
Residual Std. Error	14.79 (df = 1046)	19.95 (df = 972)	24.17 (df = 1047)	26.41 (df = 1038)	28.51 (df = 1054)

*Note: Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 1000 replications and shown in parentheses. Sample sizes differ owing to differences in exclusion for missing values in subsequent waves of the survey. *p<0.1** p<0.05p***p<0.01*

Figure 24: Densities and proportion of responses across the various waves of the Hpa An survey



Note: Density functions are represented with the red line, while proportion of responses are indicated in blue/grey bars. X-axis for all panels feature SERS resilience scores ranging from 1-5.

Table 25: Difference in differences between incomes in Baseline and Wave 5 outcomes

	Log(Income+1)	
	Unweighted (1)	IPTW (2)
f · post (Difference in Differences)	0.13 (0.09)	-0.03 (0.11)
f (1=Directly affected by flooding)	-1.04*** (0.04)	-0.96*** (0.05)
post (1=Periods after flooding)	-0.18*** (0.04)	-0.17*** (0.04)
Household fixed effects	YES	YES
Wave fixed effects	YES	YES
Observations	2,187	2,187
Adjusted R^2	0.35	0.41
Residual Std. Error (df = 1066)	0.55	0.81

*Note: Values indicate Beta coefficients with Robust Standard Errors in parentheses. Results are weighted using IPTW. *p<0.1** p<0.05p***p<0.01.*

Table 26: Difference in differences with inclusion of weather, time of day, and day of week fixed effects

	Unweighted	IPTW sample
f · post (Difference in Differences)	-0.08*** (0.02)	-0.06*** (0.02)
f (1=Directly affected by flooding)	-0.07*** (0.02)	-0.10*** (0.02)
post (1=Periods after flooding)	-0.01* (0.01)	-0.01 (0.01)
Time of day FE	YES	YES
Day of week FE	YES	YES
Weather FE	YES	YES
Wave FE	YES	YES
Village controls	YES	YES
Observations	8,241	8,241
Adjusted R2	0.30	0.30
Residual Std. Error	0.17	0.23

*Note: SERS scores are used as the outcome variable. Values indicate Beta coefficients with Robust Standard Errors in parentheses. Results are weighted using IPTW. *p<0.1** p<0.05p***p<0.01.*

Table 27: Difference-in-differences for the three resilience-related capacities used in the SERS module

	Anticipatory		Absorptive		Adaptive		Transformative	
	Unweighted	IPTW	Unweighted	IPTW	Unweighted	IPTW	Unweighted	IPTW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
f · post (Difference in Differences)	-0.07*** (0.02)	-0.05 (0.03)	-0.07*** (0.02)	-0.06*** (0.02)	-0.09*** (0.03)	-0.08** (0.03)	-0.03 (0.04)	-0.004 (0.04)
f (1=Directly affected by flooding)	-0.15*** (0.02)	-0.16*** (0.03)	-0.12*** (0.02)	-0.13*** (0.02)	-0.11*** (0.03)	-0.12*** (0.03)	-0.13*** (0.03)	-0.15*** (0.03)
post (1=Periods after flooding)	0.12*** (0.01)	0.14*** (0.02)	-0.01 (0.01)	-0.02* (0.01)	-0.13*** (0.01)	-0.11*** (0.01)	0.06*** (0.01)	0.06*** (0.01)
Household fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Wave fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	8,667	8,667	8,678	8,678	8,689	8,689	8,674	8,674
Adjusted R^2	0.18	0.16	0.26	0.27	0.19	0.19	0.08	0.12
Residual Std. Error	0.25 (df = 7539)	0.35 (df = 7539)	0.23 (df = 7550)	0.31 (df = 7550)	0.26 (df = 7561)	0.36 (df = 7561)	0.25 (df = 7546)	0.35 (df = 7546)

*Note: Values indicate Beta coefficients with Robust Standard Errors in parentheses. Results are weighted using IPTW. *p<0.1** p<0.05p***p<0.01.*

Table 28: Difference in differences with resilience-scores calculated as a combination of absorptive, adaptive and transformative capacities

	Unweighted (1)	IPTW (2)
f · post (Difference in Differences)	-0.06*** (0.02)	-0.04* (0.02)
f (1=Directly affected by flooding)	-0.12*** (0.01)	-0.14*** (0.02)
post (1=Periods after flooding)	-0.03*** (0.004)	-0.02*** (0.004)
Household fixed effects	YES	YES
Wave fixed effects	YES	YES
Observations	8,666	8,666
Adjusted R2	0.24	0.25
Residual Std. Error (df = 1066)	0.17	0.24

*Note: Values indicate Beta coefficients with Robust Standard Errors in parentheses. Results are weighted using IPTW. *p<0.1** p<0.05p***p<0.01.*

Appendix B Section 3: Testing for the impact of subsequent shocks amongst directly affected households

In our first setup, we regress resilience-over-time scores (i.e. the area under the curve for resilience scores across the panel) against the same covariates as those included in Equation 4. In addition, we interact f_{hv} (a variable for flood impact) with a dummy variable, d_{hv}, which indexes for whether the household has experienced an additional shock in any of the subsequent Waves. To account for non-random rates of drop-out amongst households affected by subsequent shocks we limit the analysis to the fully balanced dataset.

$$Resilienceovertime_{hv} = \beta_1 f_{hv} + \beta_2 d_{hv} + \beta_3 (f_{hv} \cdot d_{hv}) + \beta_4 Resilienceovertime_{hv-1} + \beta_5 s_{hv} + \beta_6 p_{hv} + \xi_v + e_{hv} \quad 1)$$

The main feature of interest is β_3, representing the effect of subsequent shocks on households directly affected by flooding (compared with those indirectly affected).

Table 29: Interactions between flood exposure and subsequent shock events

	Unweighted sample (1)	IPTW sample (2)
Dummy for additional shocks (1=Shocks) * Flood exposure (1=Directly exposed)	-12.89** (6.57)	-9.62** (4.81)
Socio-economic and risk perception FE	YES	YES
Baseline resilience FE	YES	YES
Village-level FE	YES	YES
Observations	925	925
Adjusted R^2	0.26	0.26
Residual Std. Error	27.91 (df = 899)	37.55 (df = 899)

*Note: Resilience-over-time scores (i.e. area under the curve for SERS scores over time) are used as the outcome variable. Only results of interactions are shown. Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 1000 replications and shown in parentheses. *p<0.1** p<0.05p***p<0.01*

As part of the second analysis we run a difference-in-difference-in-differences setup (akin to triple-differencing). This essentially augments Equation 1 by adding a further interaction to the original difference-in-difference estimate ($post_t \cdot f_h$). Here d_h, is a dummy variable for whether the household experienced an additional shock subsequent to the main period of flooding between the baseline and Wave 1 (1 = subsequent shock).

$$Resilience_{ht} = \beta_1 post_t + \beta_2 f_h + \beta_3 d_h + \beta_4 (post_t \cdot f_h) + \beta_5 (post_t \cdot d_h) + \beta_6 (f_h \cdot d_h) + \beta_7 (post_t \cdot f_h \cdot d_h) + \psi_h + e_{ht}$$

6)

In the context of this study, it is β_7 that is of primary interest, representing the difference between the DiD (i.e. seen in Equation) for those hit by subsequent shocks compared to those that weren't. In other words, it indicates the effect of follow-on shocks on resilience scores for households directly affected by flooding (when compared to those indirectly affected by flooding).

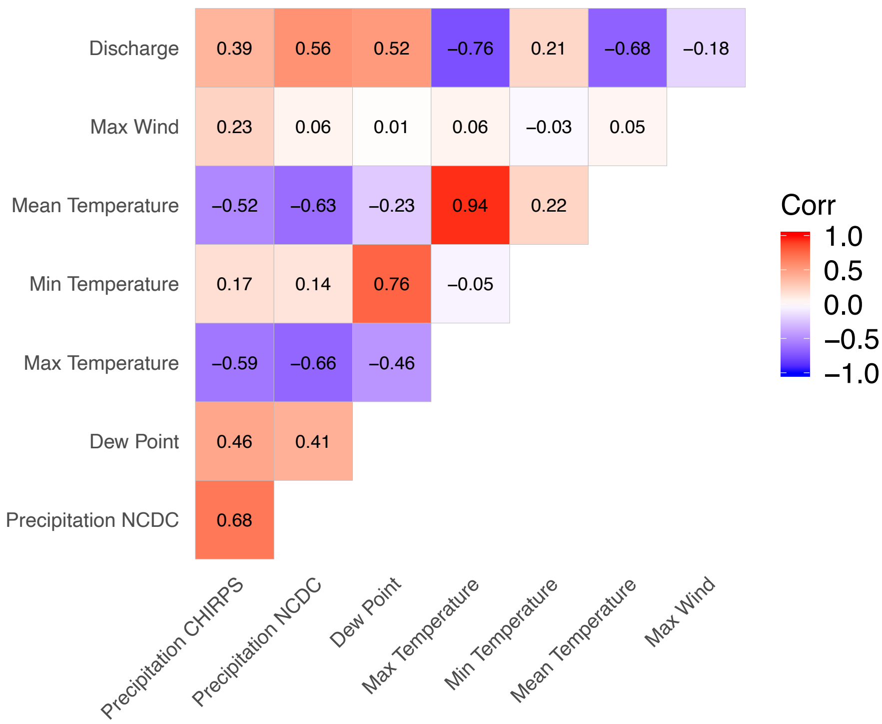
Table 30: Triple difference estimates on SERS resilience scores

	(1) Unweighted sample	(2) IPTW sample
post · f · d (Triple differences)	-0.05 (0.04)	-0.06 (0.04)
Household fixed effects	YES	YES
Wave fixed effects	YES	YES
Observations	7,512	7,512
Adjusted R^2	0.31	0.29
Residual Std. Error (df = 6563)	0.17	0.23

*Note: SERS scores are used as the outcome variable. Only results from the triple interaction are shown. Values indicate Beta coefficients and Standard Errors clustered at the village-level using a Wild cluster bootstrap with 200 replications shown in parentheses. Results in Model 2 are weighted using IPTW. *p<0.1** p<0.05p***p<0.01*

Appendix C (Chapter 4)

Figure 25: Correlations between weather variables during the survey period



Notes: Plot shows Pearson correlation coefficients for weather variables with a 3-day rolling average during the survey period.

Table 31: Associations between perceived resilience and weather: across seasons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall (log+1)	0.03*** (0.004)						0.05*** (0.01)	0.04*** (0.01)
$Rainfall^2$ (log+1)	-0.003** (0.001)						-0.01*** (0.001)	-0.003*** (0.001)
Dew Point (log+1)		-2.86* (1.60)					3.51 (2.32)	
Dew $Point^2$ (log+1)		0.50** (0.25)					-0.61 (0.37)	
Discharge			0.01*** (0.002)				0.01*** (0.003)	0.01** (0.002)
$Discharge^2$			-0.0002*** (0.0001)				-0.0001 (0.0001)	-0.0001 (0.0001)
Temperature				-0.20*** (0.02)			-0.23*** (0.03)	-0.19*** (0.03)
$Temperature^2$				0.003*** (0.0004)			0.004*** (0.001)	0.004*** (0.001)
Min Temp					0.15*** (0.02)		0.08** (0.03)	0.06*** (0.02)
Min $Temp^2$					-0.003*** (0.0005)		-0.002** (0.001)	-0.002*** (0.0005)
Max Wind (log)						0.02*** (0.01)	0.04*** (0.01)	
Max $Wind^2$ (log)						-0.0004 (0.01)	-0.001 (0.01)	
Constant	0.56*** (0.05)	4.63* (2.51)	0.64*** (0.04)	3.69*** (0.33)	-1.20*** (0.26)	0.65*** (0.05)	-2.33 (3.49)	2.45*** (0.48)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Season FE	N	N	N	N	N	N	N	N
Month FE	N	N	N	N	N	N	N	N
Observations	11,375	10,910	10,232	10,978	10,978	10,838	9,656	9,864
Adjusted R^2	0.12	0.09	0.13	0.09	0.09	0.08	0.17	0.16
Residual Std. Error	0.19 (df = 10140)	0.19 (df = 9676)	0.19 (df = 8997)	0.19 (df = 9743)	0.19 (df = 9743)	0.19 (df = 9603)	0.18 (df = 8412)	0.18 (df = 8623)

*Notes: All models include household, hour and day of the week fixed effects. Weather variables feature as 3 day rolling averages. Standard errors are clustered at the household level. *p<0.1**p<0.05***p<0.01*

Table 32: Associations between perceived resilience and weather: within seasons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall (log+1)	0.02*** (0.005)						0.01* (0.01)	0.01 (0.01)
Rainfall2 (log+1)	-0.001 (0.001)						0.0003 (0.001)	0.001 (0.001)
Dew Point (log+1)		7.09*** (1.78)					-2.15 (2.32)	
Dew Point2 (log+1)		-1.11*** (0.28)					0.32 (0.37)	
Discharge			0.02*** (0.003)				0.02*** (0.003)	0.02*** (0.003)
Discharge2			-0.001*** (0.0001)				-0.001*** (0.0001)	-0.001*** (0.0001)
Temperature				-0.02 (0.02)			-0.07** (0.03)	-0.05 (0.03)
Temperature2				0.0002 (0.0004)			0.001** (0.001)	0.001 (0.001)
Min Temp					0.13*** (0.02)		0.07** (0.03)	0.02 (0.02)
Min Temp2					-0.003*** (0.0005)		-0.001** (0.001)	-0.0004 (0.0005)
Max Wind (log)						-0.03*** (0.01)	0.002 (0.01)	
Max Wind2 (log)						-0.0001 (0.01)	-0.001 (0.01)	
Constant	0.57*** (0.05)	-10.67*** (2.79)	0.71*** (0.04)	0.99*** (0.36)	-0.99*** (0.26)	0.65*** (0.05)	4.67 (3.48)	1.30*** (0.47)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Season FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	N	N	N	N	N	N	N	N
Observations	11,375	10,910	10,232	10,978	10,978	10,838	9,656	9,864
Adjusted R2	0.13	0.12	0.22	0.12	0.12	0.12	0.21	0.22
Residual Std. Error	0.18 (df = 10139)	0.18 (df = 9674)	0.18 (df = 8995)	0.19 (df = 9741)	0.18 (df = 9741)	0.18 (df = 9601)	0.18 (df = 8410)	0.18 (df = 8621)

*Notes: All models include household, hour and day of the week fixed effects. Standard errors are clustered at the household level. *p<0.1**p<0.05***p<0.01*

Table 33: Associations between perceived resilience and weather: within months

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall (log+1)	-0.01* (0.01)						-0.02*** (0.01)	-0.02*** (0.01)
Rainfall2 (log+1)	0.003*** (0.001)						0.003* (0.001)	0.003** (0.001)
Dew Point (log+1)		1.04 (1.65)					-4.88** (2.19)	
Dew Point2 (log+1)		-0.19 (0.26)					0.77** (0.35)	
Discharge			0.01*** (0.004)				0.01** (0.004)	0.01** (0.004)
Discharge2			-0.001*** (0.0001)				-0.001*** (0.0001)	-0.001*** (0.0001)
Temperature				0.16*** (0.03)			-0.04 (0.04)	-0.03 (0.04)
Temperature2				-0.003*** (0.001)			0.001 (0.001)	0.0004 (0.001)
Min Temp					0.01 (0.02)		0.07** (0.03)	0.03 (0.02)
Min Temp2					-0.0002 (0.0005)		-0.001** (0.001)	-0.001 (0.001)
Max Wind (log)						0.01 (0.01)	-0.001 (0.01)	
Max Wind2 (log)						-0.01*** (0.01)	-0.003 (0.01)	
Constant	0.45*** (0.04)	-0.97 (2.58)	0.49*** (0.05)	-1.75*** (0.49)	0.37 (0.27)	0.44*** (0.04)	8.05** (3.26)	0.68 (0.54)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Season FE	N	N	N	N	N	N	N	N
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11,375	10,910	10,232	10,978	10,978	10,838	9,656	9,864
Adjusted R2	0.22	0.22	0.27	0.22	0.22	0.21	0.26	0.26
Residual Std. Error	0.17 (df = 10131)	0.17 (df = 966)	0.17 (df = 8987)	0.17 (df = 9733)	0.17 (df = 9733)	0.17 (df = 9593)	0.17 (df = 8402)	0.17 (df = 8613)

Notes: All models include household, hour and day of the week fixed effects. Standard errors are clustered at the household level.
*$p<0.1$ **$p<0.05$ ***$p<0.01$

Table 34: Relationship between resilience and anomalous weather conditions (measured as Z-scores)

	(1) Across-season	(2) Within-season	(3) Across-season	(4) Within-season
Rainfall Poisson Z-score	0.01*** (0.001)	0.004*** (0.001)	0.005*** (0.001)	0.003** (0.001)
Rainfall Poisson Z-score^2	0.002*** (0.0003)	0.001*** (0.0003)	0.002*** (0.0003)	0.0004 (0.0003)
Discharge Poisson Z-score	-0.03*** (0.002)	0.002 (0.003)	-0.03*** (0.002)	-0.0003 (0.003)
Discharge Poisson Z-score^2	0.01*** (0.002)	-0.0001 (0.002)	0.01*** (0.002)	0.005** (0.002)
Temperature Z-score	0.01*** (0.003)	0.03*** (0.003)	0.01*** (0.003)	0.03*** (0.003)
Temperature Z-score ^{2}	0.01*** (0.001)	0.002** (0.001)	0.003*** (0.001)	0.0004 (0.001)
Min Temp Z-score	0.02** (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.03*** (0.01)
Min Temp Z-score ^{2}	-0.02*** (0.01)	-0.02*** (0.01)	-0.01 (0.01)	-0.01 (0.005)
Dew Point Z-score	-0.001 (0.003)	-0.0000 (0.003)		
Dew Point Z-score^2	0.0000 (0.0001)	0.0001 (0.0001)		
Max Wind Poisson Z-score	-0.04*** (0.01)	-0.01 (0.01)		
Max Wind Poisson Z-score^2	0.01 (0.01)	-0.02* (0.01)		
Constant	0.63*** (0.06)	0.71*** (0.05)	0.62*** (0.06)	0.70*** (0.05)
Year FE	Y	Y	Y	Y
Season FE	N	Y	N	Y
Observations	9,656	9,656	9,864	9,864
Adjusted R2	0.13	0.21	0.13	0.21
Residual Std. Error	0.19 (df = 8412)	0.18 (df = 8410)	0.19 (df = 8623)	0.18 (df = 8621)

p<0.1p<0.05***p<0.01*

Table 35: Inclusion of controls for individual-level affect

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall (log+1)	-0.02 (0.01)	-0.01 (0.01)	-0.02 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Rainfall^2 (log+1)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.002 (0.003)	0.002 (0.003)
Dew Point (log+1)	-6.17** (2.40)	-6.57*** (2.37)	-4.31* (2.42)	-4.57* (2.39)	-2.24 (2.35)	-2.20 (2.37)
Dew Point^2 (log+1)	1.00*** (0.38)	1.06*** (0.38)	0.68* (0.39)	0.73* (0.38)	0.36 (0.38)	0.35 (0.38)
Discharge	-0.12*** (0.02)	-0.12*** (0.02)	-0.15*** (0.02)	-0.15*** (0.02)	-0.08*** (0.02)	-0.08** (0.04)
Discharge^2	0.01*** (0.001)	0.01*** (0.001)	0.01*** (0.001)	0.01*** (0.001)	0.01*** (0.002)	0.01** (0.003)
Temperature	-0.03 (0.10)	-0.01 (0.10)	-0.02 (0.10)	-0.01 (0.10)	0.01 (0.09)	0.03 (0.10)
Temperature^2	-0.0001 (0.002)	-0.0003 (0.002)	-0.0001 (0.002)	-0.0003 (0.002)	-0.0003 (0.002)	-0.001 (0.002)
Min Temp	-0.02 (0.04)	-0.02 (0.04)	0.004 (0.04)	0.001 (0.04)	0.005 (0.04)	0.002 (0.04)
Min Temp^2	0.001 (0.001)	0.001 (0.001)	0.0001 (0.001)	0.0001 (0.001)	-0.0001 (0.001)	-0.0000 (0.001)
Max Wind (log)	-0.01 (0.01)	-0.01 (0.01)	-0.02* (0.01)	-0.01* (0.01)	-0.01 (0.01)	-0.01 (0.01)
Max Wind^2 (log)	-0.01 (0.01)	-0.01 (0.01)	-0.0002 (0.01)	-0.0002 (0.01)	0.002 (0.01)	0.003 (0.01)
Happiness		0.02*** (0.005)		0.02*** (0.005)		0.02*** (0.005)
Sense of Purpose		0.02*** (0.01)		0.02*** (0.01)		0.02*** (0.005)
Life satisfaction		0.01** (0.005)		0.01** (0.005)		0.01** (0.005)
Constant	-0.02 (0.01)	-0.01 (0.01)	-0.02 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Year fixed effect	Y	Y	Y	Y	Y	Y
Season fixed effect	N	Y	N	N	Y	N
Month fixed effect	N	N	Y	N	N	Y
Observations	3,664	3,635	3,664	3,635	3,664	3,635
Adjusted R^2	0.21	0.22	0.21	0.23	0.24	0.25
Residual Std. Error	0.16 (df = 2435)	0.16 (df = 2403)	0.16 (df = 2433)	0.16 (df = 2401)	0.16 (df = 2431)	0.16 (df = 2399)

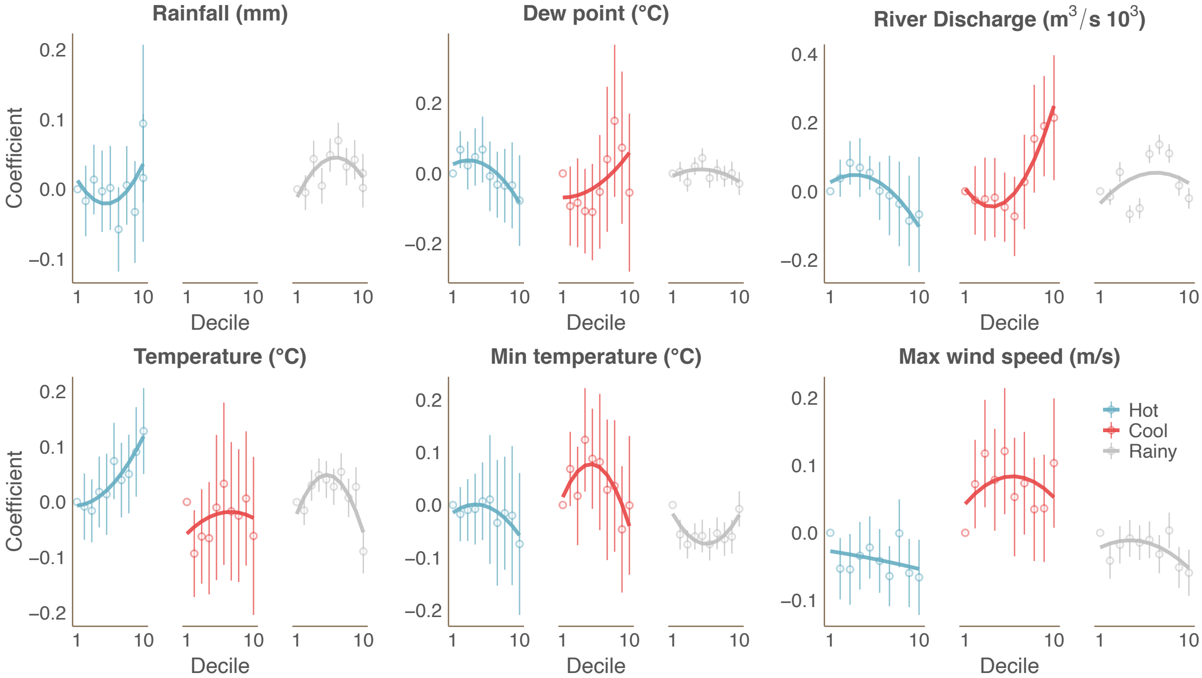
*In addition to those listed, all regressions include hour, time of day and household fixed effects. Standard errors are clustered at the household level. Measures for subjective happiness, sense of purpose and life satisfaction are measured on a scale from 1-5 (from low to high). *p<0.1; **p<0.05; ***p<0.01*

Table 36: Interactions between weather and seasonal dummies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rainfall (log +1): Rainy season	0.07*** (0.01)						0.07*** (0.03)
Rainfall (log +1)²: Rainy season	-0.02*** (0.004)						-0.03*** (0.01)
Dew Point (log +1): Rainy season (log+1)		57.14*** (13.96)					32.83* (19.60)
Dew Point (log +1): Rainy season		-8.76*** (2.16)					-4.89 (3.07)
Dew Point (log +1) ²: Cool season		11.09** (4.36)					-37.32*** (10.70)
Dew Point (log +1)²: Cool season		-1.70** (0.70)					6.07*** (1.74)
Discharge: Rainy season			0.20*** (0.05)				-0.09 (0.18)
Discharge²: Rainy season			-0.05*** (0.01)				0.01 (0.04)
Discharge: Cool season			0.22*** (0.05)				-0.11 (0.18)
Discharge²: Cool season			-0.05*** (0.01)				0.01 (0.04)
Temperature (log +1): Rainy season				0.09 (0.09)			0.58** (0.24)
Temperature (log +1) ²: Rainy season				-0.002 (0.002)			-0.01*** (0.004)
Temperature (log +1): Cool season				0.66*** (0.14)			-0.37 (0.39)
Temperature (log +1) ²: Cool season				-0.01*** (0.002)			0.01 (0.01)
Min Temp: Rainy season					-0.09 (0.07)		-0.48*** (0.13)
Min Temp²: Rainy season					0.002 (0.001)		0.01*** (0.003)
Min Temp: Cool season					0.29*** (0.07)		0.18 (0.14)
Min Temp²: Cool season					-0.01*** (0.002)		-0.004 (0.003)
Max Wind (log): Rainy season						-0.01 (0.04)	-0.02 (0.05)
Max Wind (log)²: Rainy season						-0.01 (0.02)	0.004 (0.03)
Max Wind (log): Cool season						-0.11** (0.04)	-0.05 (0.06)
Max Wind (log)²: Cool season						0.03 (0.03)	0.10*** (0.04)
Constant	0.63*** (0.05)	-2.93 (4.70)	0.90*** (0.06)	1.37 (1.01)	-0.03 (0.50)	0.62*** (0.05)	-38.98*** (11.83)
Year FE	Y	Y	Y	Y	Y	Y	Y
Season FE	Y	Y	Y	Y	Y	Y	Y
Month FE	N	N	N	N	N	N	N
Observations	11,375	10,910	10,232	10,978	10,978	10,838	9,656
Adjusted R2	0.14	0.13	0.22	0.14	0.12	0.12	0.23
Residual Std. Error	0.18 (df = 10134)	0.18 (df = 9670)	0.18 (df = 8991)	0.18 (df = 9737)	0.18 (df = 9737)	0.18 (df = 9597)	0.17 (df = 8386)

*Notes: All models include household, hour and day of the week fixed effects. Only outputs from interaction terms are shown. Rainfall excludes the cool season owing to few periods of rainfall during the season. Standard errors are clustered at the household level. *p<0.1**p<0.05***p<0.01*

Figure 26: Coefficient plots of associations between resilience and aggregated weather variables across seasons



Notes: Plotted outputs match Eq. 2, with subsets for each of Myanmar's three seasons. Panels show results from separate regression models with each respective weather observation replaced by binned deciles (all other variables are identical to the setup in Eq. 2). Dots represent beta coefficients for binned deciles for each respective weather observation, with horizontal lines showing 95% confidence intervals. Outputs in blue are restricted to observations in the Hot season, outputs are restricted to observations in the Cool season and outputs in grey are restricted to observations in the Rainy season. All models include day of the week, hour of the day, seasonal and year fixed effects. Lines are shown as quadratic polynomial trends. All regressions feature standard errors clustered at the household level.

Annex C Section 1

Below I document a number of additional robustness checks and wider analyses alongside those described in Section 4.5.

Given the large number of missing values included in the NCDC precipitation variable (26% of the sample in the survey timeseries) the CHIRPS dataset was used in each of the preferred model specifications. Despite this, Annex C Figure 27 compares the two variables revealing close associations between the two measures. To test the implications of using CHIRPS in the main analysis, I repeat Eq. 2 with data from the original NCDC dataset. Appendix C Table 37 shows that separate analyses using NCDC and CHIRPS appear to be largely consistent and in line with the paper's main findings.

Observations for dew point and wind speed have higher rates of missing values throughout the Hpa An dataset. There is also high correlation between dew point and minimum temperature (see Appendix C Figure 25). As such, I redo the main specification with humidity and wind speed removed. Appendix C Tables 31, 32 and 33 (Model 8 for all tables) shows that results are largely consistent across the different specifications.

To examine the effects of alternative clustering strategies I re-run the main analyses with standard errors clustered at the village level in Appendix C Table 38. Given that there are only 8 villages in the survey, I use a Clustered Wild Bootstrap with 200 replications, as per Cameron et al. (2008).

Another point of interest is in examining heterogenous effects across genders. Indeed, insights from subjective wellbeing suggest that females may be more responsive to weather and seasonal shifts (Connolly 2013; Fedderson et al. 2013). Accordingly, the main analysis is re-run sub-setting for male and female respondents in Appendix C Table 39. Differences in significance levels are noticed for some variables, though by and large associations and trends between the two are matched. Areas of divergence relate mainly to the within-month model and may be suggestive of shorter-term gendered differences (or cognitive biases). We can also test for heterogeneous effects across livelihood types. Appendix C Table 40 has a similar setup, sub-setting for households that derive their livelihood primary through farming or otherwise. Here again we see slight differences, though the two groups are largely matched in terms of the nature of resilience-climate relationships. Interestingly, levels of significance are particularly pronounced for non-farmer livelihoods.

It is possible that results may be skewed by heavy seasonal flooding experienced in Hpa An over the course of the first two waves of the survey (as per Chapter 3). Yet, when data from these initial waves is removed, similar associations between the outcomes between full and reduced samples are apparent (see Annex C Table 41. Similarly, I also test the results against different variants of the SERS model, each corresponding to alternative resilience frameworks in the wider literature (see Galappaththi et al. 2019). Appendix C Table 42 shows how use of frameworks made up of Adaptive, Absorptive and Transformative capacities (referred to as the AAT model modelled on Béné et al. 2012) as well as all four capacities combined (4C model) affect the outcomes of the main regression. Here strong associations between resilience and weather are seen across all framework variants.

Lastly, it is important to consider whether associations are driven by the immediate effects of weather during the exact period of interview, or whether they instead reflected longer-term lags (i.e. weather over a number of days prior to the interview). Recall that in the main analyses a 3-day rolling average is used. This reflects the fact that a household's resilience capacities are unlikely to fluctuate on a day-to-day basis. To look at this assumption in more detail I recreate Eq. 2 using a number of different specifications for the moving average of weather variables. Specifically, I add a 7-day rolling average as well as weather on the day of the interview (essentially a 1-day model).

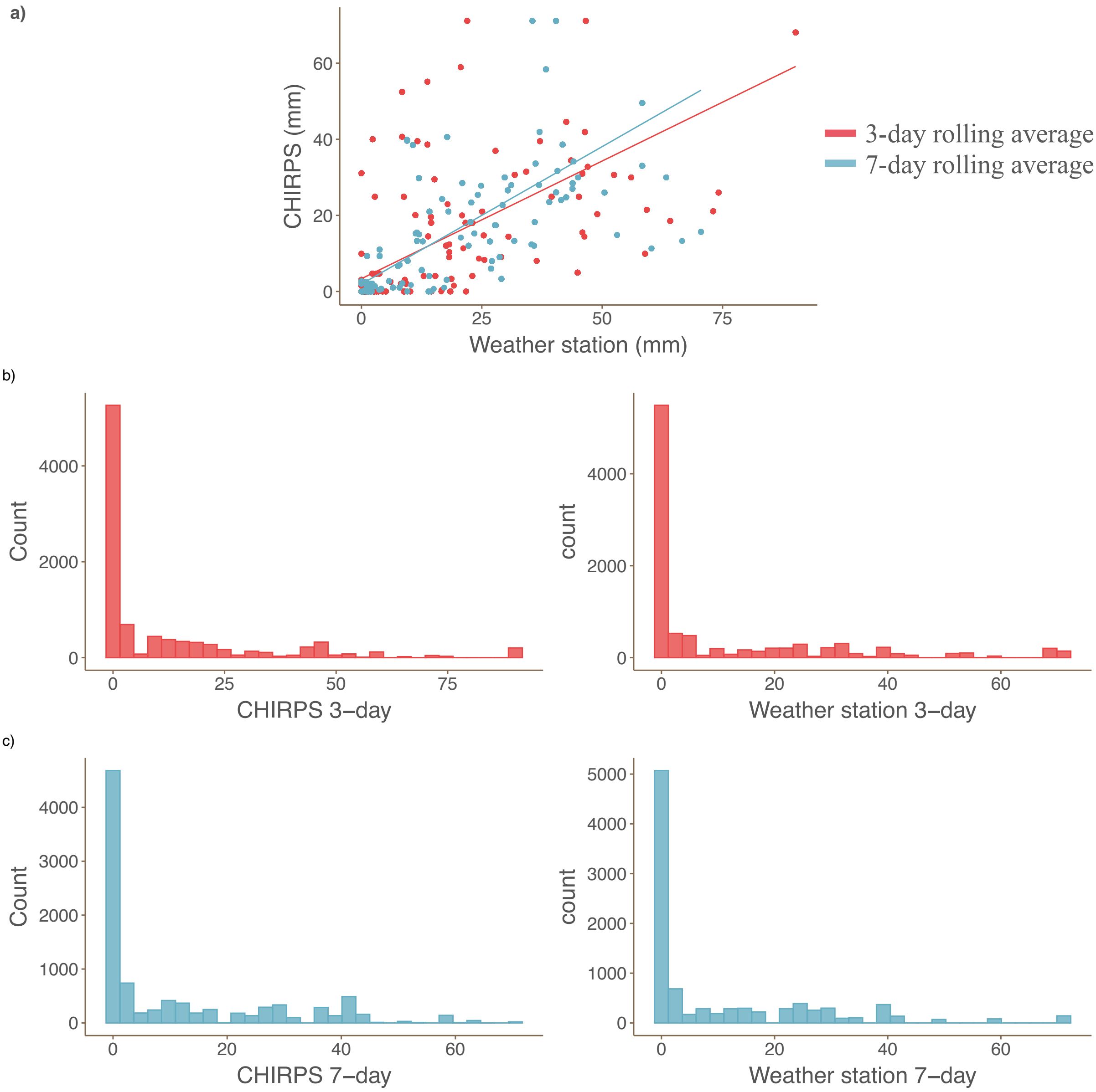
Results from models showcasing binned deciles for each of the weather variables are presented in Annex C Figure 28. Here we see that effects and trends differ across the three modes. In most cases, the 1-day models generally exhibit weaker associations between resilience and the weather variables of interest – both with regards to the magnitude of effect sizes and levels of statistical significance – relative to the 3- and 7-day variants. This may suggest that the impacts on resilience are likely to be more pronounced across longer-term periods (again hinting at stronger seasonal influences). Exceptions can be seen with regards to humidity and river discharge where the 1-day models also exhibit strong relationships with resilience alongside the other two variants. In some cases, associations differ in terms of sign between different models, suggesting heterogenous effects across time. Care should therefore be taken in considering the cumulative effects across different time periods – with further exploratory analyses (both qualitative and qualitative) needed to uncover potential drivers and mechanisms.

Table 37: Comparison between NCDC and CHIRPS rainfall datasets

	(1)	(2)	(3)	(4)	(5)	(6)
NCDC Rainfall (log+1)	0.08***		0.02		0.02*	
	(0.01)		(0.01)		(0.01)	
NCDC Rainfall2 (log+1)	-0.01***		-0.001		-0.004	
	(0.002)		(0.002)		(0.002)	
CHIRPS Rainfall (log+1)		0.02***		-0.02***		-0.01
		(0.01)		(0.01)		(0.01)
CHIRPS Rainfall2 (log+1)		-0.002		0.004***		0.001
		(0.001)		(0.001)		(0.001)
Dew Point (log+1)	-5.13***	-6.02***	-6.84***	-6.37***	-1.21	-0.69
	(1.67)	(1.57)	(1.71)	(1.60)	(1.82)	(1.63)
Dew Point2 (log+1)	0.84***	0.99***	1.11***	1.03***	0.19	0.11
	(0.27)	(0.25)	(0.27)	(0.26)	(0.29)	(0.26)
Discharge	-0.01**	-0.001	0.01***	0.02***	0.02***	0.02***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.01)	(0.004)
Discharge2	0.0004***	0.0002**	-0.0004***	-0.001***	-0.001***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Temperature	0.03	-0.01	0.04	0.04	-0.002	0.003
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Temperature2	-0.0001	0.0003	-0.001	-0.001	0.0001	-0.0001
	(0.001)	(0.0005)	(0.001)	(0.0005)	(0.001)	(0.001)
Min Temp	-0.05*	0.01	-0.02	-0.02	-0.03	-0.03
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
Min Temp2	0.001	-0.0003	0.0004	0.0004	0.001	0.001
	(0.001)	(0.0005)	(0.001)	(0.0005)	(0.001)	(0.0005)
Max Wind (log)	0.05***	0.04***	0.02**	0.004	-0.001	-0.004
	(0.01)	(0.01)	(0.01)	(0.005)	(0.01)	(0.01)
Max Wind2 (log)	-0.02***	-0.01***	-0.001	-0.01	-0.01	-0.01
	(0.01)	(0.004)	(0.01)	(0.004)	(0.01)	(0.004)
Constant	8.66***	9.83***	11.23***	10.36***	2.94	1.88
	(2.46)	(2.37)	(2.53)	(2.40)	(2.74)	(2.47)
Year FE	Y	Y	Y	Y	Y	Y
Season FE	N	Y	N	N	Y	N
Month FE	N	N	Y	N	N	Y
Observations	6,495	8,479	6,495	8,479	6,495	8,479
Adjusted R2	0.15	0.14	0.21	0.21	0.24	0.25
Residual Std. Error	0.18 (df = 5265)	0.18 (df = 7243)	0.18 (df = 5263)	0.18 (df = 7241)	0.17 (df = 5255)	0.17 (df = 7233)

*Notes: All models include household, hour and day of the week fixed effects. Standard errors are clustered at the household level. *p<0.1**p<0.05***p<0.01*

Figure 27: Comparison between CHIRPS and weather station observations for precipitation



Notes: Panel a) is a scatter-plot of the two different precipitation variables. Panels b) and c) are histograms comparing 3- and 7-day rolling averages between the precipitation variables. Missing values in all cases are removed.

Table 38: Comparison of weather and resilience with errors clustered at the Village level

	(1)	(2)	(3)
Rainfall (log+1)	0.05*** (0.01)	0.01 (0.01)	-0.02*** (0.01)
Rainfall2 (log+1)	-0.01*** (0.002)	0.0003 (0.001)	0.003** (0.001)
Dew Point (log+1)	3.51 (3.80)	-2.15 (3.69)	-4.88 (2.97)
Dew Point2 (log+1)	-0.61 (0.61)	0.32 (0.59)	0.77 (0.48)
Discharge	0.75** (0.32)	1.70*** (0.32)	1.08*** (0.28)
Discharge2	-1.29 (1.18)	-5.48*** (1.20)	-6.23*** (0.90)
Temperature	-0.23*** (0.05)	-0.07 (0.05)	-0.04 (0.05)
Temperature2	0.004*** (0.001)	0.001 (0.001)	0.001 (0.001)
Min Temp	0.08*** (0.01)	0.07*** (0.02)	0.07*** (0.02)
Min Temp2	-0.002*** (0.0003)	-0.001*** (0.0003)	-0.001*** (0.0004)
Max Wind (log)	0.04*** (0.01)	0.002 (0.01)	-0.001 (0.01)
Max Wind2 (log)	-0.001 (0.01)	-0.001 (0.01)	-0.003 (0.004)
Constant	-2.33 (6.02)	4.67 (5.69)	8.05* (4.36)
Year FE	Y	Y	Y
Season FE	N	Y	N
Month FE	N	N	Y
Observations	9,656	9,656	9,656
Adjusted R2	0.17	0.21	0.26
Residual Std. Error	0.18 (df = 8412)	0.18 (df = 8410)	0.17 (df = 8402)

Notes: All models include household, hour and day of the week fixed effects. Standard errors are clustered at the Village level using a clustered wild bootstrap (200 replications) from the multiwayvcov package in R. *Panel is fully balanced with rows removed if any weather variables have missing values. *p<0.1**p<0.05***p<0.01*

Table 39: Comparison of associations between resilience and weather across genders

	(1) Male	(2) Female	(3) Male	(4) Female	(3) Male	(4) Female
Rainfall (log+1)	0.05***	0.05***	0.01	0.01	-0.01*	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Rainfall² (log+1)	-0.01***	-0.01***	0.0002	0.001	0.002	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dew Point (log+1)	6.40*	0.80	-0.24	-4.17	-3.28	-6.74**
	(3.40)	(3.09)	(3.38)	(3.14)	(3.22)	(3.00)
Dew Point² (log+1)	-1.05*	-0.19	0.02	0.63	0.51	1.06**
	(0.54)	(0.49)	(0.54)	(0.50)	(0.51)	(0.48)
Discharge	0.01***	0.01	0.02***	0.02***	0.02**	0.01
	(0.004)	(0.004)	(0.004)	(0.004)	(0.01)	(0.01)
Discharge²	-0.0002	-0.0001	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Temperature	-0.20***	-0.27***	-0.05	-0.10**	0.02	-0.10*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Temperature²	0.004***	0.005***	0.001	0.002*	-0.0004	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Min Temp	0.02	0.15***	0.02	0.13***	0.01	0.15***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)
Min Temp²	-0.001	-0.003***	-0.001	-0.002***	-0.0003	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Max Wind (log)	0.03***	0.04***	-0.004	0.01	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Max Wind² (log)	0.001	-0.002	0.003	-0.004	0.003	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-6.87	1.69	1.61	7.53	5.26	10.91**
	(5.13)	(4.64)	(5.07)	(4.69)	(4.82)	(4.46)
Year FE	Y	Y	Y	Y	Y	Y
Season FE	N	N	Y	Y	N	N
Month FE	N	N	N	N	Y	Y
Observations	5,026	4,630	5,026	4,630	5,026	4,630
Adjusted R^2	0.16	0.17	0.21	0.22	0.25	0.28
Residual Std. Error	0.18 (df = 4361)	0.18 (df = 4010)	0.18 (df = 4359)	0.18 (df = 4008)	0.17 (df = 4351)	0.17 (df = 4000)

*Notes: All models include household, hour and day of the week fixed effects. Standard errors are clustered at the household level. *p<0.1**p<0.05***p<0.01*

Table 40: Comparison of associations between resilience and weather across livelihood types

	(1) Farmer	(2) Non-Farmer	(3) Farmer	(4) Non-Farmer	(5) Farmer	(6) Non-Farmer
Rainfall (log+1)	0.05*** (0.01)	0.05*** (0.01)	0.01 (0.01)	0.01 (0.01)	-0.02** (0.01)	-0.02** (0.01)
Rainfall² (log+1)	-0.004** (0.002)	-0.01*** (0.002)	0.002 (0.002)	-0.001 (0.002)	0.003 (0.002)	0.002 (0.002)
Dew Point (log+1)	-0.63 (3.70)	6.26** (2.99)	-7.53** (3.63)	1.79 (3.05)	-7.33** (3.42)	-2.58 (2.84)
Dew Point² (log+1)	0.07 (0.59)	-1.06** (0.48)	1.21** (0.58)	-0.33 (0.49)	1.18** (0.55)	0.38 (0.45)
Discharge	0.0004 (0.005)	0.01*** (0.003)	0.01** (0.005)	0.02*** (0.004)	0.01 (0.01)	0.02*** (0.01)
Discharge²	0.0002 (0.0002)	-0.0004*** (0.0001)	-0.0002 (0.0002)	-0.001*** (0.0001)	-0.0003 (0.0002)	-0.001*** (0.0002)
Temperature	-0.18*** (0.05)	-0.26*** (0.04)	-0.01 (0.05)	-0.12** (0.05)	-0.01 (0.06)	-0.06 (0.06)
Temperature²	0.003*** (0.001)	0.005*** (0.001)	0.0001 (0.001)	0.002** (0.001)	0.0002 (0.001)	0.001 (0.001)
Min Temp	0.08 (0.05)	0.07* (0.04)	0.06 (0.05)	0.06* (0.04)	0.05 (0.05)	0.08** (0.04)
Min Temp²	-0.002* (0.001)	-0.001* (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002** (0.001)
Max Wind (log)	0.01 (0.01)	0.06*** (0.01)	-0.03** (0.01)	0.02** (0.01)	-0.02 (0.01)	0.01 (0.01)
Max Wind2 (log)	0.02* (0.01)	-0.02** (0.01)	0.01 (0.01)	-0.01* (0.01)	0.002 (0.01)	-0.01 (0.01)
Constant	3.28 (5.51)	-6.11 (4.53)	11.97** (5.39)	-0.80 (4.60)	11.60** (5.06)	4.62 (4.27)
Year FE	Y	Y	Y	Y	Y	Y
Season FE	N	N	Y	Y	N	N
Month FE	N	N	N	N	Y	Y
Observations	4,087	5,569	4,087	5,569	4,087	5,569
Adjusted R^2	0.16	0.17	0.21	0.21	0.26	0.26
Residual Std. Error	0.18 (df = 3542)	0.18 (df = 4828)	0.18 (df = 3540)	0.18 (df = 4826)	0.17 (df = 3532)	0.17 (df = 4818)

*Notes: All models include household, hour and day of the week fixed effects. Standard errors are clustered at the household level. *p<0.1**p<0.05***p<0.01*

Table 41: Regression output comparing full sample with reduced sample (minus Waves 1 and 2)

	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) Reduced Sample	(5) Reduced Sample	(6) Reduced Sample
Rainfall (log+1)	0.05*** (0.01)	0.01* (0.01)	-0.02*** (0.01)	0.04*** (0.01)	0.01* (0.01)	-0.01 (0.01)
Rainfall² (log+1)	-0.01*** (0.001)	0.0003 (0.001)	0.003* (0.001)	-0.01*** (0.002)	-0.002 (0.002)	-0.0003 (0.002)
Dew Point (log+1)	3.51 (2.32)	-2.15 (2.32)	-4.88** (2.19)	-7.34** (2.87)	-12.25*** (2.96)	-9.40*** (3.07)
Dew Point² (log+1)	-0.61 (0.37)	0.32 (0.37)	0.77** (0.35)	1.18** (0.46)	1.98*** (0.48)	1.50*** (0.50)
Discharge	0.01*** (0.003)	0.02*** (0.003)	0.01** (0.004)	0.004 (0.004)	0.02*** (0.01)	0.01 (0.01)
Discharge²	-0.0001 (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)	0.0001 (0.0002)	-0.001*** (0.0002)	-0.0000 (0.0002)
Temperature	-0.23*** (0.03)	-0.07** (0.03)	-0.04 (0.04)	-0.11** (0.05)	-0.003 (0.05)	0.02 (0.05)
Temperature²	0.004*** (0.001)	0.001** (0.001)	0.001 (0.001)	0.002*** (0.001)	0.0002 (0.001)	-0.0004 (0.001)
Min Temp	0.08** (0.03)	0.07** (0.03)	0.07** (0.03)	0.30*** (0.05)	0.25*** (0.05)	0.02 (0.06)
Min Temp²	-0.002** (0.001)	-0.001** (0.001)	-0.001** (0.001)	-0.01*** (0.001)	-0.01*** (0.001)	-0.001 (0.001)
Max Wind (log)	0.04*** (0.01)	0.002 (0.01)	-0.001 (0.01)	0.05*** (0.01)	0.005 (0.01)	-0.002 (0.01)
Max Wind² (log)	-0.001 (0.01)	-0.001 (0.01)	-0.003 (0.01)	-0.02** (0.01)	-0.004 (0.01)	-0.01 (0.01)
Constant	-2.33 (3.49)	4.67 (3.48)	8.05** (3.26)	9.87** (4.23)	16.79*** (4.34)	14.34*** (4.46)
Year FE	Y	Y	Y	Y	Y	Y
Season FE	N	Y	N	N	Y	N
Month FE	N	N	Y	N	N	Y
Observations	9,656	9,656	9,656	6,730	6,730	6,730
Adjusted R2	0.17	0.21	0.26	0.16	0.19	0.22
Residual Std. Error	0.18 (df = 8412)	0.18 (df = 8410)	0.17 (df = 8402)	0.18 (df = 5511)	0.18 (df = 5509)	0.17 (df = 5502)

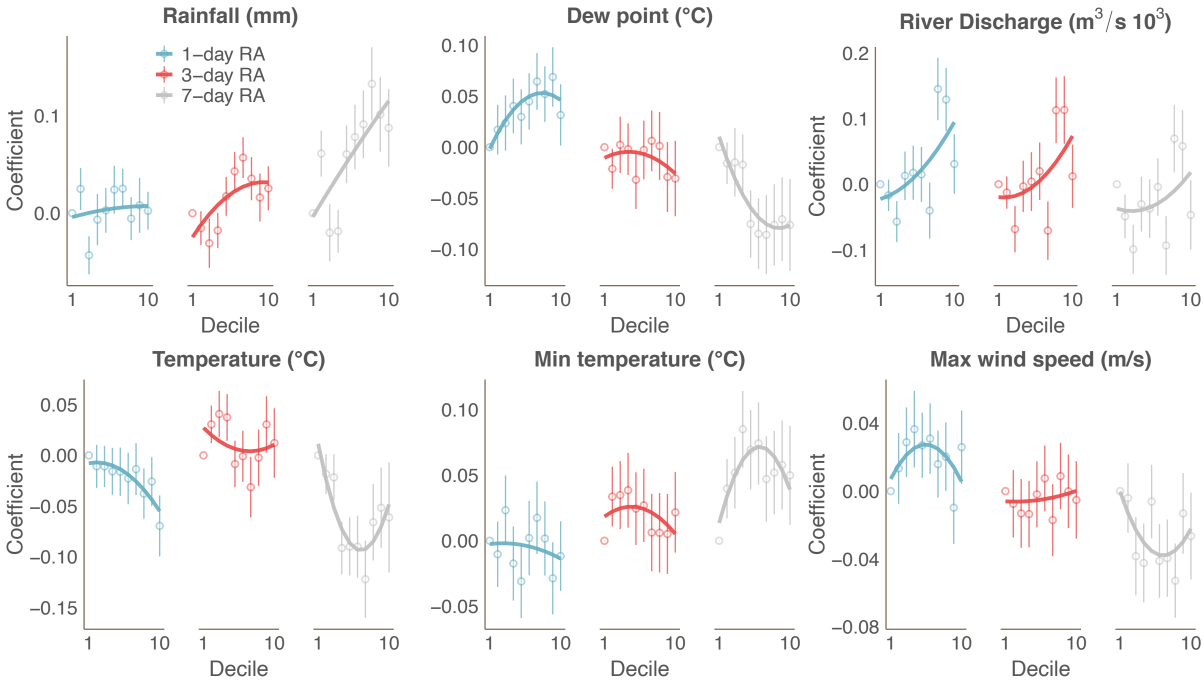
*Models 1-3 include the full sample of household. Models 3-6 omit waves 1 and 2 of the sample. In addition to those listed, all regressions include hour, time of day and household fixed effects. Standard errors are clustered at the household level *p<0.1; **p<0.05; ***p<0.01*

Table 42: Regression output comparing different variants of SERS module

	(1) 3A	(2) 3A	(3) 3A	(4) 4C	(5) 4C	(6) 4C	(7) AAT	(8) AAT	(9) AAT
Rainfall (log+1)	0.05*** (0.01)	0.01* (0.01)	-0.02*** (0.01)	0.04*** (0.005)	0.005 (0.01)	-0.02*** (0.01)	0.04*** (0.01)	-0.002 (0.01)	-0.02*** (0.01)
Rainfall^2 (log+1)	-0.01*** (0.001)	0.0003 (0.001)	0.003* (0.001)	-0.004*** (0.001)	0.001 (0.001)	0.003*** (0.001)	-0.003*** (0.001)	0.003** (0.001)	0.004*** (0.001)
Dew Point (log+1)	3.51 (2.32)	-2.15 (2.32)	-4.88** (2.19)	1.82 (2.02)	-2.98 (2.04)	-5.17** (2.02)	0.45 (2.34)	-3.59 (2.37)	-5.77** (2.41)
Dew Point^2 (log+1)	-0.61 (0.37)	0.32 (0.37)	0.77** (0.35)	-0.33 (0.32)	0.46 (0.33)	0.82** (0.32)	-0.10 (0.37)	0.56 (0.38)	0.91** (0.38)
Discharge	0.01*** (0.003)	0.02*** (0.003)	0.01** (0.004)	0.01*** (0.002)	0.02*** (0.003)	0.01*** (0.004)	0.003 (0.003)	0.01*** (0.003)	0.01*** (0.004)
Discharge^2	-0.0001 (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.0002** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.0001 (0.0001)	-0.0004*** (0.0001)	-0.001*** (0.0001)
Temperature	-0.23*** (0.03)	-0.07** (0.03)	-0.04 (0.04)	-0.20*** (0.03)	-0.07** (0.03)	-0.04 (0.04)	-0.22*** (0.03)	-0.10*** (0.03)	-0.07 (0.04)
Temperature^2	0.004*** (0.001)	0.001** (0.001)	0.001 (0.001)	0.004*** (0.001)	0.001* (0.001)	0.001 (0.001)	0.004*** (0.001)	0.002*** (0.001)	0.001 (0.001)
Min Temp	0.08** (0.03)	0.07** (0.03)	0.07** (0.03)	0.06** (0.03)	0.05* (0.03)	0.07** (0.03)	0.08*** (0.03)	0.08*** (0.03)	0.08** (0.03)
Min Temp^2	-0.002** (0.001)	-0.001** (0.001)	-0.001** (0.001)	-0.001** (0.001)	-0.001* (0.001)	-0.001** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002** (0.001)
Max Wind (log)	0.04*** (0.01)	0.002 (0.01)	-0.001 (0.01)	0.04*** (0.01)	0.004 (0.01)	0.001 (0.01)	0.03*** (0.01)	-0.01 (0.01)	0.001 (0.01)
Max Wind^2 (log)	-0.001 (0.01)	-0.001 (0.01)	-0.003 (0.01)	-0.003 (0.01)	-0.003 (0.01)	-0.003 (0.01)	0.01 (0.01)	0.005 (0.01)	-0.01 (0.01)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Season FE	N	Y	N	N	Y	N	N	Y	N
Month FE	N	N	Y	N	N	Y	N	N	Y
Observations	9,656	9,656	9,656	9,646	9,646	9,646	9,668	9,668	9,668
Adjusted R2	0.17	0.21	0.26	0.16	0.20	0.24	0.14	0.18	0.22
Residual Std. Error	0.18 (df = 8412)	0.18 (df = 8410)	0.17 (df = 8402)	0.16 (df = 8402)	0.16 (df = 8400)	0.16 (df = 8392)	0.18 (df = 8424)	0.18 (df = 8422)	0.17 (df = 8414)

*Models 1-3 include the full sample of household. Models 3-6 omit waves 1 and 2 of the sample. In addition to those listed, all regressions include hour, time of day and household fixed effects. Standard errors are clustered at the household level *p<0.1; **p<0.05; ***p<0.01*

Figure 28: Associations between weather and resilience using alternative moving averages



Notes: Plotted outputs match Eq. 2, except that 1-day, 3-day and 7-day moving averages for weather values are used in models for the blue, red and grey values respectively. Panels show results from separate regression models with each respective weather observation replaced by binned deciles (all other variables are identical to the setup in Eq. 2). Dots represent beta coefficients for binned deciles for each respective weather observation, with horizontal lines showing 95% confidence intervals. Outputs in blue include month and year fixed effects, outputs in red feature season and year fixed effects and outputs in grey have year fixed effects. All models include day of the week, hour of the day, season and year fixed effects. Lines are shown as quadratic polynomial trends. All regressions feature standard errors clustered at the household level.

Table 43: Comparison between subjectively-evaluated resilience and weather (across and within seasons) for Mudon site

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rainfall (log+1)	-0.05*					0.11*	-0.06**					0.16***
	(0.03)					(0.06)	(0.03)					(0.06)
Rainfall² (log+1)	0.01					-0.03	0.02***					-0.05***
	(0.01)					(0.02)	(0.01)					(0.02)
Dew Point (log+1)		5.41				7.03		1.09				11.46
		(3.84)				(11.52)		(5.04)				(13.58)
Dew Point² (log+1)		-0.95				-1.01		-0.24				-1.78
		(0.61)				(1.83)		(0.81)				(2.17)
Temperature			-0.47***			-0.59			-0.65***			-1.35***
			(0.16)			(0.45)			(0.18)			(0.50)
Temperature²			0.01***			0.01			0.01***			0.02***
			(0.003)			(0.01)			(0.003)			(0.01)
Min Temp				0.13**		-0.24				0.11**		-0.23
				(0.05)		(0.18)				(0.05)		(0.21)
Min Temp²				-0.003***		0.004				-0.003***		0.005
				(0.001)		(0.004)				(0.001)		(0.005)
Max Wind (log)					0.01	0.11**					0.02	0.09*
					(0.02)	(0.05)					(0.06)	(0.05)
Max Wind² (log)					0.06**	-0.10					0.01	-0.18**
					(0.03)	(0.07)					(0.02)	(0.08)
Constant	0.60***	-7.24	7.05***	-0.66	0.51***	-0.64	0.62***	-0.69	9.97***	-0.49	0.50	3.65
	(0.02)	(6.01)	(2.31)	(0.55)	(0.02)	(20.07)	(0.03)	(7.79)	(2.59)	(0.55)	(23.35)	(23.35)
Season FE	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	N	N	N	N	N	N
Observations	2,121	2,230	2,519	2,519	2,519	1,915	2,121	2,230	2,519	2,519	2,519	1,915
Adjusted R2	0.03	0.06	0.03	0.05	0.03	0.06	0.05	0.07	0.05	0.06	0.04	0.07
Residual Std. Error	0.18 (df = 1352)	0.19 (df = 1454)	0.19 (df = 1741)	0.19 (df = 1741)	0.19 (df = 1741)	0.18 (df = 1138)	0.18 (df = 1348)	0.19 (df = 1451)	0.19 (df = 1738)	0.19 (df = 1738)	0.19 (df = 1738)	0.18 (df = 1135)

*Notes: All models include household, hour and day of the week fixed effects. Standard errors are clustered at the household level. *p<0.1**p<0.05***p<0.01*

References

Adger, W. N. (1999). Social vulnerability to climate change and extremes in coastal Vietnam. *World development*, *27*(2), 249-269.

Adger, W. N. (2000). Social and ecological resilience: are they related?. Progress in human geography, 24(3), 347-364. doi: 10.1191/030913200701540465

Adger, W. N., Kelly, P. M., Winkels, A., Huy, L. Q., & Locke, C. (2002). Migration, remittances, livelihood trajectories, and social resilience. *AMBIO: A Journal of the Human Environment*, 31(4), 358-366.

Adger, W. N., Arnell, N. W., & Tompkins, E. L. (2005a). Successful adaptation to climate change across scales. *Global environmental change*, *15*(2), 77-86. DOI: https://doi.org/10.1016/j.gloenvcha.2004.12.005

Adger, W. N., Hughes, T. P., Folke, C., Carpenter, S. R., & Rockström, J. (2005b). Social-ecological resilience to coastal disasters. *Science*, 309(5737), 1036-1039.

Adger, W. N., Brown, K., Nelson, D. R., Berkes, F., Eakin, H., Folke, C., ... & Ruitenbeek, J. (2011). Resilience implications of policy responses to climate change. *Wiley Interdisciplinary Reviews: Climate Change*, *2*(5), 757-766.

Agard, J., Schipper, E.L.F., Birkmann, J., Campos, M., Dubeux, C., Nojiri, Y., Olsson, L., Osman-Elasha, B., Pelling, M., Prather, M.J., Rivera-Ferre, M.G., Ruppel, O.C., Sallenger, A., Smith, K.R., St. Clair, A.L., Mach, K.J., Mastrandrea, M.D & Eren Bilir, T. (2014). *Glossary*. IPCC Fifth Assessment Report. Intergovernmental Panel on Climate Change (IPCC). Geneva: Switzerland.

Akamani, K., & Hall, T. E. (2015). Determinants of the process and outcomes of household participation in collaborative forest management in Ghana: A quantitative test of a community resilience model. *Journal of environmental management*, *147*, 1-11.

Aldrich, D. P. (2012). *Building resilience: Social capital in post-disaster recovery*. University of Chicago Press.

Aldrich, D. P., & Meyer, M. A. (2015). Social capital and community resilience. *American behavioral scientist*, *59*(2), 254-269.

Aldunce P., Beilin R., Howden M., and Handmer J. (2015). Resilience for disaster risk management in a changing climate: Practitioners' frames and practices. *Global Environmental Change*, 30, 1-11. DOI: https://doi.org/10.1016/j.gloenvcha.2014.10.010

Alexander, D. E. (2013). Resilience and disaster risk reduction: an etymological journey. *Natural hazards and earth system sciences*, *13*(11), 2707-2716. DOI: https://doi.org/10.5194/nhess-13-2707-2013

Alfani, F., Dabalen, A., Fisker, P., & Molini, V. (2015). Can we measure resilience? A proposed method and evidence from countries in the Sahel. World Bank. Washington D.C.: USA

Alfieri, L., Burek, P., Dutra, E., Krzeminski, B., Muraro, D., Thielen, J., & Pappenberger, F. (2013). GloFAS-global ensemble streamflow forecasting and flood early warning. *Hydrology and Earth System Sciences*, 17(3), 1161.

Alinovi, L., Mane, E., & Romano, D. (2008). Towards the measurement of household resilience to food insecurity: applying a model to Palestinian household data. Deriving Food Security Information From National Household Budget Surveys. Experiences, Achievement, Challenges. FAO. Rome, 137-52.

Allison, E. H., & Ellis, F. (2001). The livelihoods approach and management of small-scale fisheries. *Marine policy*, 25(5), 377-388.

Anuradha, J. M. P. N., Fujimura, M., Inaoka, T., & Sakai, N. (2019). Role of Social and Human Capital in Household Resilience: Empirical Evidence from an Agricultural Village Community with Exposure to Significant Environmental Stresses in Sri Lanka. *Global Social Welfare*, 1-12.

Anderson, B. G., & Bell, M. L. (2009). Weather-related mortality: how heat, cold, and heat waves affect mortality in the United States. *Epidemiology* (Cambridge, Mass.), 20(2), 205.

Angrist, J., & Pischke, J. (2008). Mostly harmless econometrics: An empiricist's companion. Chapter 5. Princeton, NJ: Princeton University Press.

Apanovich, N., & Mazur, R. E. (2018). Determinants of seasonal food security among smallholder farmers in south-central Uganda. *Agriculture & Food Security*, 7(1), 1-10.

Arouri, M., Nguyen, C., & Youssef, A. B. (2015). Natural disasters, household welfare, and resilience: evidence from rural Vietnam. *World development*, *70*, 59-77.

Aung, Lai Lai et al. (2017). Myanmar Climate Report. Department of Meteorology and Hydrology, Ministry of Transport and Communications, Government of the Republic of the Union of Myanmar, and Norwegian Meteorological Institute. Naypyidaw: Myanmar.

Ayeb-Karlsson, S., van der Geest, K., Ahmed, I., Huq, S., & Warner, K. (2016). A people-centred perspective on climate change, environmental stress, and livelihood resilience in Bangladesh. Sustainability Science, 11(4), 679-694.

Badjeck, M. C., Allison, E. H., Halls, A. S., & Dulvy, N. K. (2010). Impacts of climate variability and change on fishery-based livelihoods. *Marine policy*, 34(3), 375-383.

Bahadur, A. V., Ibrahim, M., & Tanner, T. (2013). Characterising resilience: unpacking the concept for tackling climate change and development. *Climate and Development*, *5*(1), 55-65.

Bahadur, A. V., Peters, K., Wilkinson, E., Pichon, F., Gray, K. and Tanner, T. (2015) The 3As: tracking resilience across BRACED. Working and Discussion Papers. London: Overseas Development Institute.

Bahadur, A., and F. Pichon. (2017). Analysis of resilience measurement frameworks and approaches. Overseas Development Institute, London, UK. [online] URL: http://www.preventionweb.net/publications/view/52589

Béné C., Al-Hassan RM., Amarasinghe O., Fong P., Ocran J., Onumah E., Ratuniata R., Van Tuyen T., McGregor JA & Mills DJ. (2016a). Is resilience socially constructed? Empirical evidence from Fiji, Ghana, Sri Lanka, and Vietnam. *Global Environmental Change*, 38, pp.153-170. DOI: https://doi.org/10.1016/j.gloenvcha.2016.03.005

Béné, C., Frankenberger, T., Langworthy, M., Mueller, M. & Martin, S. (2016b). The Influence of Subjective and Psycho-social Factors on People's Resilience: Conceptual Framework and Empirical Evidence. Report prepared by the Technical Consortium, a project of the CGIAR. Technical Report Series No. 2: Strengthening the Evidence Base for Resilience in the Horn of Africa. A joint International Livestock Research Institute (ILRI) and TANGO International publication. Nairobi: Kenya

Béné, C., Wood, R. G., Newsham, A. and Davies, M. (2012) Resilience: new utopia or new tyranny? Reflection about the potentials and limits of the concept of resilience in relation to vulnerability reduction programmes. Working Paper 2012(405). Brighton: Institute of Development Studies.

Béné, C., Frankenberger, T., Griffin, T., Langworthy, M., Mueller, M., & Martin, S. (2019). 'Perception matters': New insights into the subjective dimension of resilience in the context of humanitarian and food security crises. *Progress in Development Studies*, 19(3), 186-210.

Berkes, F., & Turner, N. J. (2006). Knowledge, learning and the evolution of conservation practice for social-ecological system resilience. *Human ecology*, 34(4), 479.

Berman, R., Quinn, C., & Paavola, J. (2012). The role of institutions in the transformation of coping capacity to sustainable adaptive capacity. *Environmental Development*, *2*, 86-100.

Berman, R., Quinn, C., & Paavola, J. "Identifying drivers of household coping strategies to multiple climatic hazards in Western Uganda: implications for adapting to future climate change." *Climate and Development* 7.1 (2015): 71-84.

Bertrand, M., Duflo, E., & Mullainathan, S.(2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, 119(1), 249–275. doi: 10.1162/003355304772839588

Bhatta, G. D., & Aggarwal, P. K. (2016). Coping with weather adversity and adaptation to climatic variability: a cross-country study of smallholder farmers in South Asia. *Climate and Development*, *8*(2), 145-157.

Birkmann, J. (2006) 'Measuring vulnerability to promote disaster-resilient societies: conceptual frameworks and definitions', Towards Disaster Resilient Societies 1: 9–54.

Bonanno, G. A., Galea, S., Bucciarelli, A., & Vlahov, D. (2007). What predicts psychological resilience after disaster? The role of demographics, resources, and life stress. *Journal of consulting and clinical psychology*, *75*(5), 671.

Borquez, R., Aldunce, P., & Adler, C. (2017). Resilience to climate change: from theory to practice through co-production of knowledge in Chile. *Sustainability science*, 12(1), 163-176.

Bottazzi, P., Winkler, M., Boillat, S., Diagne, A., Maman Chabi Sika, M., Kpangon, A., ... & Speranza, C. (2018). Measuring Subjective Flood Resilience in Suburban Dakar: A Before–After Evaluation of the "Live with Water" Project. *Sustainability*, *10*(7), 2135.

Bours, D., McGinn, C., & Pringle, P. (2014). Monitoring & evaluation for climate change adaptation and resilience: A synthesis of tools, frameworks and approaches. SEA Change Community of Practice and UKCIP. Oxford: UK.

Brenkert, A. L., & Malone, E. L. (2005). Modeling vulnerability and resilience to climate change: a case study of India and Indian states. *Climatic Change*, *72*(1-2), 57-102.

Brooks, N., Anderson, S., Ayers, J., Burton, I., & Tellam, I. (2011) Tracking adaptation and measuring development. IIED. London: UK.

Brooks, N., Anderson, S., Burton, I., Fisher, S., Rai, N., & Tellam, I. (2013). An operational framework for tracking adaptation and measuring development (TAMD). International Institute for Environment and Development. London: UK.

Brooks, N., Faget, D., Hiejkoop. P. (2019). Tools for measuring resilience in Nepal: Literature Review. Department for International Development: Expert Advisory Call Down Services. London: UK. Accessible at: https://assets.publishing.service.gov.uk/media/5cff7c18e5274a3cc494e7b1/Resilience_measurement_LitRev_FINAL-updated1_ML_June_2019.pdf

Brown, K. (2014). Global environmental change I: A social turn for resilience?. *Progress in human geography*, *38*(1), 107-117.

Brown, K., (2015). *Resilience, development and global change*. Routledge.

Buikstra, E., Ross, H., King, C. A., Baker, P. G., Hegney, D., McLachlan, K., and Rogers-Clark, C. (2010). The components of resilience—Perceptions of an Australian rural community. *Journal of Community Psychology*, 38.8., 975-991. DOI: https://doi.org/10.1002/jcop.20409

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, *90*(3), 414-427.

Canavan, J. (2008). Resilience: Cautiously welcoming a contested concept. *Child Care in Practice*, *14*(1), 1-7.

Cannon, T., & Müller-Mahn, D. (2010). Vulnerability, resilience and development discourses in context of climate change. *Natural hazards*, *55*(3), 621-635.

Cantril, H. (1965). *The pattern of human concerns*. New Brunswick, NJ: Rutgers University Press.

CARE. (2009). CVCA handbook (climate vulnerability and capacity analysis). Care International. London: UK. Accessible at: http://careclimatechange.org/wp-content/uploads/2014/12/cvca_en.pdf

Carpenter, S., Walker, B., Anderies, J. M., & Abel, N. (2001). From metaphor to measurement: resilience of what to what?. *Ecosystems*, *4*(8), 765-781.

Carr, E. R. (2005). Development and the household: Missing the point?. *GeoJournal*, 62(1-2), 71-83.

Carr, E. R. (2019). Properties and projects: Reconciling resilience and transformation for adaptation and development. *World Development*, 122, 70-84.

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2004). Shocks, sensitivity and resilience: Tracking the economic impacts of environmental disaster on assets in Ethiopia and Honduras. BASIS Research Program on Poverty, Inequality and Development. Washington, DC: US Agency for International Development.

Chambers, R., Longhurst, R., & Pacey, A. (1981). *Seasonal dimensions to rural poverty*. Frances Pinter.

Chesterman, S., Lamanna, C., Kalamatianou, S., & Rosenstock, T. (2017). Collecting development data with mobile phones: Key considerations from a review of the evidence. Climate Change, Agriculture and Food Security (CCAFS) CGIAR. Accessible at: https://cgspace.cgiar.org/rest/bitstreams/145616/retrieve

Choptiany, J.M., Phillips, S., Graeub, B. E., Colozza, D., Settle, W., Herren, B., & Batello, C. (2016). SHARP: integrating a traditional survey with participatory self-evaluation and learning for climate change resilience assessment. Climate and Development, 1-13. DOI: https://doi.org/10.1080/17565529.2016.1174661

Cisse, J.D., Barrett, C.B., (2015). Estimating development resilience: A conditional moments-based approach. Working Paper, Cornell University.

Claire, A., Graber, R., Jones, L., Conway, D. (2017). Subjective measures of climate resilience: what is the added value for policy and programming? Global Environmental Change, 46 pp17-22. DOI: https://doi.org/10.1016/j.gloenvcha.2017.07.001

Clare, A., Sagynbekova, L., Singer, G., Bene, B. & Rahmanberdi, A (2018) Can subjective resilience indicators predict future food security? Evidence from three communities in rural Kyrgyzstan. Centre for Climate Change Economics and Policy Working Paper 342/Grantham Research Institute on Climate Change and the Environment Working Paper 308. London: London School of Economics and Political Science

Coates, J., Rogers, B., Webb, P., Maxwell, D., Houser, R., & McDonald, C. (2007). "Diet Diversity Study." Final report to the World Food Programme. Friedman School of Nutrition Science and Policy, Tufts University. Medford: USA

Cobb-Clark, D. A., & Schurer, S. (2012). The stability of big-five personality traits. *Economics Letters*, 115(1), 11-15.

Cohen, L., Manion, L., & Morrison, K. (2002). Research methods in education. Routledge. UK

Connor, K.M. & Davidson, J.R. (2003). Development of a new resilience scale: The Connor-Davidson resilience scale (CD-RISC). *Depression and anxiety*, 18(2), pp.76-82. DOI: https://doi.org/10.1002/da.10113

Constas, M., Cisse, J., Knippenberg, E. & Downie, K. (2016). A Focused Review of Methodologies to Measure Resilience: An Analysis of Conceptual Presentations, Indicators, and Estimation Procedures. Report prepared by The Technical Consortium, a project of the CGIAR. Technical Report Series No 2: Strengthening the Evidence Base for Resilience in the Horn of Africa. Nairobi, Kenya: A joint International Livestock Research Institute (ILRI) and Charles H. Dyson School of Applied Economics and Management, College of Agriculture and Life Sciences, Cornell University publication. Ithica: United States

Constas, M., Frankenberger, T. R., Hoddinott, J., Mock, N., Romano, D., Bene, C., & Maxwell, D. (2014). *A common analytical model for resilience measurement—Causal framework and methodological options Resilience Measurement Technical Working Group*. FSiN Technical Series Paper No, 2, 52.

COSA. (2017). Simpler Resilience Measurement: Tools to Diagnose and Improve How Households Fare in Difficult Circumstances from Conflict to Climate Change. *The Committee on Sustainability Assessment*. Philadelphia, USA: Accessible at: https://thecosa.org/wp-content/uploads/2018/04/COSA-FORD-Simpler-Resilience-Measurement-Full-20180413.pdf

Cote, M., & Nightingale, A. J. (2012). Resilience thinking meets social theory: situating social change in socio-ecological systems (SES) research. *Progress in Human Geography*, *36*(4), 475-489.

Cox, R. S. and Perry, K. M. E. (2011) 'Like a fish out of water: reconsidering disaster recovery and the role of place and social capital in community disaster resilience', American Journal of Community Psychology 48(3–4): 395–411.

Crane, T. (2010). Of models and meanings: cultural resilience in social–ecological systems. *Ecology and Society*, *15*(4). DOI: https://doi.org/10.5751/es-03683-150419

Cummins, R. A., Eckersley, R., Pallant, J., Van Vugt, J., & Misajon, R. (2003). Developing a national index of subjective wellbeing: The Australian Unity Wellbeing Index. *Social indicators research*, 64(2), 159-190. DOI: https://doi.org/10.1023/a:1024704320683

Cundill, G., Currie-Alder, B., & Leone, M. (2019). The future is collaborative. *Nature Climate Change*, 1.

Cunguara, B., and B. Kelly, 2009: The impact of the PARPA II in promoting the agricultural sector in rural Mozambique. Working Paper, Ministry of Planning and Development, Maputo, Mozambique, 27 pp. [Available online at http://www.open.ac.uk/technology/mozambique/sites/www.open.ac.uk.technology.mozambique/files/pics/d119369.pdf.]

Cutter, S. L. (2016). The landscape of disaster resilience indicators in the USA. *Natural hazards*, *80*(2), 741-758.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E. and Webb, J. (2008) 'A place-based model for understanding community resilience to natural disasters', Global Environmental Change 18(4): 598–606

Cutter, S. L., Burton, C. G., & Emrich, C. T. (2010). Disaster resilience indicators for benchmarking baseline conditions. *Journal of Homeland Security and Emergency Management*, *7*(1).

D'Errico, M. & Giuseppe S. (2014). A dynamic analysis of resilience in Uganda. Food and Administration Organisation. United Nations Food and Agriculture Organisation. Rome: Italy.

D'Errico, M., & Di Giuseppe, S. (2018). Resilience mobility in Uganda: A dynamic analysis. *World Development*, 104, 78-96.

D'Errico, M., Grazioli, F., and Pietrelli, R. (2017) "Cross-country Evidence of the Relationship Between Resilience and the Subjective Perception of Well-being and Social Inclusion: Evidence from the Regions of Matam (Senegal) and the Triangle of Hope (Mauritania)." *Journal of International Development*. https://doi.org/10.1002/jid.3335

D'Errico, M., Letta, M., Montalbano, P., & Pietrelli, R. (2019). Resilience thresholds to temperature anomalies: a long-run test for rural Tanzania. *Ecological Economics*, 164, 106365.

Dabalen, A., Etang, A., Hoogeveen, J., Mushi, E., Schipper, Y., & von Engelhardt, J. (2016). *Mobile Phone Panel Surveys in Developing Countries: A Practical Guide for Microdata Collection*. The World Bank.

de Perez, E. C., van den Hurk, B., van Aalst, M., Jongman, B., Klose, T., & Suarez, P. (2014). Forecast-based financing: an approach for catalyzing humanitarian action based on extreme weather and climate forecasts. *Nat Hazards Earth Syst Sci Discuss*, 2(5), 3193-3218.

Deshingkar, Priya. (2012). Environmental risk, resilience and migration: implications for natural resource management and agriculture. *Environmental Research Letters* 7.1: 015603.

Devereux, S., Sabates-Wheeler, R., & Longhurst, R. (2013). *Seasonality revisited: new perspectives on seasonal poverty*. In Seasonality, Rural Livelihoods and Development (pp. 18-38). Routledge.

DFID. (2016). Measuring *resilience. Evidence on Demand report commissioned for the Department for International Development by Crown Agents. London* UK. DOI: http://dx.doi.org/10.12774/eod_tg.may2016.sturgess2

Díaz-Delgado, R., Lloret, F., Pons, X., & Terradas, J. (2002). Satellite evidence of decreasing resilience in Mediterranean plant communities after recurrent wildfires. *Ecology*, *83*(8), 2293-2303.

Diener, E. (2000). Subjective well-being: The science of happiness and a proposal for a national index. *American psychologist*, *55*(1), 34. DOI: https://doi.org/10.1037//0003-066x.55.1.34

Diener, E. (2006). Guidelines for national indicators of subjective well-being and ill-being. *Journal of happiness studies*, *7*(4), 397-404. DOI: https://doi.org/10.1007/s10902-006-9000-y

Diener, E. (2012) New findings and future directions for subjective well-being research. *American psychologist* 67.8: 590. DOI: https://doi.org/10.1037/a0029541

Djalante, R., & Thomalla, F. (2010). Community resilience to natural hazards and climate change impacts: a review of definitions and operational frameworks. 5th Annual International Workshop & Expo on Sumatra Tsunami Disaster & Recovery

Dolan, P., & Kavetsos, G. (2016). Happy talk: Mode of administration effects on subjective well-being. *Journal of happiness studies*, *17*(3), 1273-1291.

Dolan, P., & Metcalfe, R. (2012). Measuring subjective wellbeing: Recommendations on measures for use by national governments. *Journal of social policy*, *41*(2), 409-427. DOI: https://doi.org/10.1017/s0047279411000833

Dolan, P., Layard, R., & Metcalfe, R. (2011). Measuring subjective well-being for public policy. Office For National Statistics. Newport: UK

Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of economic psychology*, *29*(1), 94-122.

Durayappah, A. (2011). The 3P model: A general theory of subjective well-being. *Journal of Happiness Studies*, *12*(4), 681-716. DOI: https://doi.org/10.1007/s10902-010-9223-9

Eckhardt, M. (2001). Symptoms and Diagnostics in Clinical BPH Quantitative analyses of interactions among symptom scores, quality of life score, voiding data and urodynamic findings. Doctoral dissertation. Utrecht University, The Netherlands. Accessible at: https://dspace.library.uu.nl/bitstream/handle/1874/433/full.pdf

Emerton, R., Zsoter, E., Arnal, L., Cloke, H. L., Muraro, D., Prudhomme, C., ... & Pappenberger, F. (2018). Developing a global operational seasonal hydro-meteorological forecasting system: GloFAS-Seasonal v1. 0. *Geoscientific Model Development*, *11*, 3327-3346.

Etherton, J., Lawson, M., & Graham, R. (2014). Individual and gender differences in subjective and objective indices of pain: gender, fear of pain, pain catastrophizing and cardiovascular reactivity. *Applied psychophysiology and biofeedback*, *39*(2), 89-97.

FAO. (2016). RIMA 2: Resilience Index Measurement and Analysis 2. United Nations Food and Agriculture Organisation. Rome: Italy. URL: http://www.fao.org/3/a-i5665e.pdf

FAO and OPM. 2018. Food security, resilience and well-being analysis of refugees and host communities in Northern Uganda. Rome: Italy.

Few, R., Morchain, D., Spear, D., Mensah, A., & Bendapudi, R. (2017). Transformation, adaptation and development: relating concepts to practice. Palgrave Communications, 3, 17092.

Fiksel, J. (2006). Sustainability and resilience: toward a systems approach. *Sustainability: Science, Practice and Policy*, *2*(2), 14-21.

Fisher, M., Reimer, J. J., & Carr, E. R. (2010). Who should be interviewed in surveys of household income?. *World Development*, 38(7), 966-973.

Fletcher, D., & Sarkar, M. (2013). Psychological resilience: A review and critique of definitions, concepts, and theory. *European Psychologist*, *18*(1), 12.

Folke C., Carpenter SR., Walker B., Scheffer M., Chapin T., Rockström J. (2010). Resilience thinking: integrating resilience, adaptability and transformability. Ecology and Society. 15.4. Accessed 1st August 2015. www.ecologyandsociety.org/vol15/iss4/art20/. DOI: https://doi.org/10.5751/es-03610-150420

Folke, C. (2006). Resilience: The emergence of a perspective for social–ecological systems analyses. *Global environmental change*, *16*(3), 253-267.

Folke, C., Carpenter, S., Elmqvist, T., Gunderson, L., Holling, C. S., & Walker, B. (2002). Resilience and sustainable development: building adaptive capacity in a world of transformations. *AMBIO: A journal of the human environment*, *31*(5), 437-441.

Foster, K. A. (2007) A case study approach to understanding regional resilience. Working Paper. Buffalo, NY: UB Institute.

Frankenberger, T., Mueller M., Spangler T., & Alexander S. (2013). Community Resilience: Conceptual Framework and Measurement Feed the Future Learning Agenda. Rockville, MD: Westat.

Frankenberger, Timothy R., and M. Katherine McCaston. (1998) The household livelihood security concept. *Food Nutrition and agriculture*. 30-35.

FSIN. (2014a). A Common Analytical Model for Resilience Measurement. Food Security Information Network. Rome: Italy. Accessible at: http://www.fsincop.net/fileadmin/user_upload/fsin/docs/resources/FSIN_Paper2_WEB_1dic%20(WEB).pdf

FSIN. (2014b). Resilience measurement principles: toward an agenda for measurement design. Food Security Information Network: Resilience Measurement Technical Working Group. Rome: Italy. Accessible at: http://www.fao.org/fileadmin/user_upload/drought/docs/FSIN%20Resilience%20Measurement%20201401.pdf

Fukuoka, Y., Rankin, S. H., & Carroll, D. L. (2007). Systematic bias in self-reported annual household incomes among unpartnered elderly cardiac patients. *Applied Nursing Research*, 20(4), 205-209.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., ... & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific data*, *2*, 150066.

Gaillard, J. C. (2010). Vulnerability, capacity and resilience: perspectives for climate and development policy. *Journal of International Development*, 22.2., 218-232. DOI: https://doi.org/10.1002/jid.1675

Galappaththi, E. K., Ford, J. D., & Bennett, E. M. (2019). A framework for assessing community adaptation to climate change in a fisheries context. *Environmental science & policy*, 92, 17-26.

Gartrell, B. (1985). Searching for "The Roots of Famine: The Case of Karamoja, *Review of African Political Economy*. 33: 102-10.

Gasparrini, A. (2016). Modelling lagged associations in environmental time series data: a simulation study. *Epidemiology* (Cambridge, Mass.), 27(6), 835.

Gibson, D. G., Pereira, A., Farrenkopf, B. A., Labrique, A. B., Pariyo, G. W., & Hyder, A. A. (2017). Mobile phone surveys for collecting population-level estimates in low-and middle-income countries: a literature review. *Journal of medical Internet research*, *19*(5).

Gonçalves, S., & White, H. (2004). Maximum likelihood and the bootstrap for nonlinear dynamic models. *Journal of Econometrics*, *119*(1), 199-219.

Government of Myanmar (GoM). (2017a). The 2014 Myanmar population and housing census: thematic report on education. Department of Population Ministry of Labour, Immigration and Population. Nay Pyi Taw: Myanmar.

Government of Myanmar (GoM). (2017b). The 2014 Myanmar population and housing census: thematic report on gender dimensions. Department of Population Ministry of Labour, Immigration and Population. Nay Pyi Taw: Myanmar.

Gregowski, R., Dorgan, A., Hutchins, C. (2017). Resilience measurement-MEL approaches in practice: Challenges and lessons in operationalizing resilience measurement frameworks – experience and lessons from cop stakeholders. Resilience Measurement Evidence and Learning, Community of Practice. New York: USA. Accessible at: http://www.measuringresilience.org/wp-content/uploads/2017/12/ITAD_Report.pdf

Hagen-Zanker, J., Postel, H., & Vidal, E. M. (2017). Poverty, migration and the 2030 Agenda for Sustainable Development. Briefing Paper. London: Overseas Development Institute.

Hall TE, Slothower M. (2009). Cognitive factors affecting homeowners' reactions to defensible space in the Oregon coast range. *Society and Natural Resources*, 22:95–110.

Helliwell, J. F., & Barrington-Leigh, C. P. (2010). Measuring and understanding subjective well-being. *Canadian Journal of Economics/Revue canadienne d'économique*, *43*(3), 729-753. DOI: https://doi.org/10.1111/j.1540-5982.2010.01592.x

Herrera, H. (2017). Resilience for Whom? The Problem Structuring Process of the Resilience Analysis. *Sustainability*, *9*(7), 1196. DOI: https://doi.org/10.3390/su9071196

Hills, T., Pramova, E., Neufeldt, H., Ericksen, P., Thornton, P. K., Noble, A., ... & McCartney, M. P. (2015). A monitoring instrument for resilience. CGIAR Research Program on Climate Change Agriculture and Food Security. Copenhagen, Denmark.

Hogarth, R. M., Portell, M., Cuxart, A., & Kolev, G. I. (2011). Emotion and reason in everyday risk perception. *Journal of Behavioral Decision Making*, *24*(2), 202-222.

Holling CS . (1973). Resilience and stability of ecological systems. Annu Rev Ecol Syst. doi:10.1146/annurev.es.04.110173.000245

Hopkins, D. J., & King, G. (2010). Improving anchoring vignettes: Designing surveys to correct interpersonal incomparability. *Public Opinion Quarterly*, *74*(2), 201-222. DOI: https://doi.org/10.1093/poq/nfq011

HSSAI. (2015). Measuring for Results: Application of Key Concepts to Resilience Measurement. *Homeland Security Studies And Analysis Institute (HSSAI).* Falls Church: USA. Accessible at: https://www.anser.org/docs/reports/HSSAI_Report-MeasuringforResults-ApplicationofKeyConceptstoResilienceMeasurement-10-12-15.pdf

Hughes, K., & Bushell, H. (2013). A multidimensional approach to measuring resilience. Oxfam. Oxford: UK. Accessible at: http://policy-practice.oxfam.org.uk/publications/a-multidimensional-approach-to-measuring-resilience-302641

Ibarrarán, M. E., Ruth, M., Ahmad, S., & London, M. (2009). Climate change and natural disasters: macroeconomic performance and distributional impacts. *Environment, development and sustainability*, *11*(3), 549-569.

IFAD. (2015). How to do measuring resilience. International Fund for Agriculture and Development (IFAD). Rome: Italy. Accessible at: https://www.uncclearn.org/sites/default/files/inventory/ifad07062016_how_to_do_measuring_climate_resilience.pdf

Ingram, J. C., Franco, G., Rumbaitis-del Rio, C., & Khazai, B. (2006). Post-disaster recovery dilemmas: challenges in balancing short-term and long-term needs for vulnerability reduction. *Environmental Science & Policy*, *9*(7-8), 607-613.

IPCC. (2001). Appendix B: Glossary of Terms: Working Group II: Impacts, Adaptation and Vulnerability. Intergovernmental Panel on Climate Change. Geneva: Switzerland

IPCC. (2007). Appendix I: Glossary: WG2. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change. Geneva: Switzerland

Jabeen, H., Johnson, C., & Allen, A. (2010). Built-in resilience: learning from grassroots coping strategies for climate variability. *Environment and Urbanization*, *22*(2), 415-431.

Jeans, H., Castillo, G. E., & Thomas, S. (2017). Absorb, Adapt, Transform: Resilience capacities. *Oxfam Great Britain*. Oxford: UK. Accessible at: https://oxfamilibrary.openrepository.com/bitstream/handle/10546/620178/gd-resilience-capacities-absorb-adapt-transform-250117-en.pdf?sequence=4&isAllowed=y

Jones L., Ludi E., and Levine S. (2010). Towards a characterisation of adaptive capacity: a framework for analysing adaptive capacity at the local level, Overseas Development Institute. London: UK

Jones, L., & Tanner, T. (2015). Measuring 'Subjective Resilience': Using Peoples' Perceptions to Quantify Household Resilience. Overseas Development Institute (ODI). London: UK

Jones, L., & Samman, E. (2016). Measuring subjective household resilience: Insights from Tanzania. Overseas Development Institute (ODI). London: England.

Jones, L., & Tanner, T. (2017). 'Subjective resilience': using perceptions to measure household resilience to climate extremes and disasters. *Regional Environmental Change*. 17. pp 229–243. DOI: https://doi.org/10.1007/s10113-016-0995-2

Jones, L. (2018a). New methods in resilience measurement: early insights from a mobile phone panel survey in Myanmar using subjective tools. Overseas Development Institute. London: UK. Accessible at: http://www.braced.org/contentAsset/raw-data/20a0886a-4975-45a5-8a83-339618dc9bf8/attachmentFile

Jones, L. (2018b). Resilience isn't the same for all: Comparing subjective and objective approaches to resilience measurement. *Wiley Interdisciplinary Reviews: Climate Change*, e552.

Jones, L., Ballon, P., von Englehardt, J. (2018a). How does resilience change over time? Tracking post-disaster recovery using mobile phone surveys. Overseas Development Institute (ODI). London:UK

Jones, L., & Samman, E. (2016). Measuring subjective household resilience: insights from Tanzania. Overseas Development Institute (ODI). London: UK.

Jones, L., Samman, E., & Vinck, P. (2018b). Subjective measures of household resilience to climate variability and change: insights from a nationally representative survey of Tanzania. *Ecology and Society,* 23(1): 9).

Jones, L., & D'Errico, M. (2019). Resilient, but from whose perspective?: like-for-like comparisons of objective and subjective measures of resilience. *World Development.*

Jordaan, A. J., Sakulski, D. M., Mashimbye, C., & Mayumbe, F. (2018). Measuring Drought Resilience Through Community Capitals. In *Resilience* (pp. 105-115). Elsevier.

Kahn, M. E. (2005). The death toll from natural disasters: the role of income, geography, and institutions. *Review of economics and statistics*, *87*(2), 271-284.

Kahneman, D. (2000). Experienced Utility and Objective Happiness: A Moment-Based Approach. In *Choices, Values and Frames*. New York: Cambridge University Press and the Russell Sage Foundation

Kahneman, D., & Krueger, A. B. (2006). Developments in the measurement of subjective well-being. *The journal of economic perspectives*, *20*(1), 3-24. DOI: https://doi.org/10.1257/089533006776526030

Kahneman, D., and Tversky, A. (1979), "Prospect Theory: An Analysis of Decision under Risk," Econometrica, 47, 263-291.

Kämpfer, S., & Mutz, M. (2013). On the sunny side of life: Sunshine effects on life satisfaction. *Social Indicators Research*, *110*(2), 579-595.

Kappes, M. S., Keiler, M., von Elverfeldt, K., & Glade, T. (2012). Challenges of analyzing multi-hazard risk: a review. *Natural hazards*, *64*(2), 1925-1958.

Kates, R. W., Travis, W. R., and Wilbanks, T. J. (2012). Transformational adaptation when incremental adaptations to climate change are insufficient. *Proceedings of the National Academy of Sciences*, 109.19., 7156-7161. DOI: https://doi.org/10.1073/pnas.1115521109

Keck, M., & Sakdapolrak, P. (2013). What is social resilience? Lessons learned and ways forward. *Erdkunde*, 5-19.

Keil, A., Zeller, M., Wida, A., Sanim, B., & Birner, R. (2008). What determines farmers' resilience towards ENSO-related drought? An empirical assessment in Central Sulawesi, Indonesia. *Climatic Change*, *86*(3-4), 291.

Kelman, I., Gaillard, J. C., & Mercer, J. (2015). Climate change's role in disaster risk reduction's future: Beyond vulnerability and resilience. *International Journal of Disaster Risk Science*, *6*(1), 21-27.

Kim, H., & Marcouiller, D. W. (2016). Natural disaster response, community resilience, and economic capacity: A case study of coastal Florida. *Society & Natural Resources*, *29*(8), 981-997.

Kimball, M., Nunn, R., & Silverman, D. (2015). *Accounting for Adaptation in the Economics of Happiness* (No. w21365). National Bureau of Economic Research. Cambridge: USA.

Kimetrica. (2015). *Measuring climate resilience and vulnerability: A case study from Ethiopia*. Nairobi: Kenya: Kimetrica. Retrieved from http://www.fsincop.net/fileadmin/user_upload/fsin/docs/resources/Pilot%20Resilience%20Study%20Executive%20Summary.pdf

King, G., & Wand, J. (2006). Comparing incomparable survey responses: Evaluating and selecting anchoring vignettes. *Political Analysis*, *15*(1), 46-66. DOI: https://doi.org/10.1093/pan/mpl011

King, G., & Wand, J. (2007). Comparing incomparable survey responses: Evaluating and selecting anchoring vignettes. *Political Analysis*, 15(1), 46-66.

Knippenberg, E., Jensen, N., & Constas, M. (2019). Quantifying household resilience with high frequency data: Temporal dynamics and methodological options. *World Development*, 121, 1-15.

Kotzee, I., & Reyers, B. (2016). Piloting a social-ecological index for measuring flood resilience: A composite index approach. *Ecological Indicators*, *60*, 45-53.

Kristoffersen, I. (2017). The metrics of subjective wellbeing data: An empirical evaluation of the ordinal and cardinal comparability of life satisfaction scores. *Social Indicators Research*, *130*(2), 845-865.

Labrique, A., Blynn, E., Ahmed, S., Gibson, D., Pariyo, G., & Hyder, A. A. (2017). Health surveys using mobile phones in developing countries: automated active strata monitoring and other statistical considerations for improving precision and reducing biases. *Journal of medical Internet research*, *19*(5).

Lavrakas, P. J. (2008). *Encyclopedia of survey research methods*. Sage Publications.

Layard, R. (2005). Happiness: Lessons from a new science. *Allen Lane. London: UK*

Lazzaroni, S., & van Bergeijk, P. A. (2014). Natural disasters' impact, factors of resilience and development: A meta-analysis of the macroeconomic literature. *Ecological Economics*, *107*, 333-346.

Lenz, E. R., & Shortridge-Baggett, L. M. (2002). *Self-efficacy in nursing: research and measurement perspectives*. Springer Publishing Company.

Levine, S. (2010). An unromantic look at pastoralism in karamoja: How hard-hearted economics shows that pastoral systems remain the solution, and not the problem. *Nomadic Peoples*, 14(2), 147-153.

Levine, S. (2014). *Assessing resilience: why quantification misses the point,* Humanitarian Policy Group, Overseas Development Institute. Available online at: http://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/9049.pdf

Lockwood, M., Raymond, C.M., Oczkowski, E., & Morrison, M. (2015). Measuring the dimensions of adaptive capacity: a psychometric approach. *Ecology and Society* 20.1.: 37. DOI: https://doi.org/10.5751/es-07203-200137

Longhurst, R., Chambers, R., & Swift, J. (1986). Seasonality and poverty: implications for policy and research. *IDS Bulletin*, 17(3), 67-71.

Lucas, R. E., & Lawless, N. M. (2013). Does life seem better on a sunny day? Examining the association between daily weather conditions and life satisfaction judgments. *Journal of personality and social psychology*, *104*(5), 872.

Magis, K. (2010) 'Community resilience: an indicator of social sustainability', Society and Natural Resources 23(5): 401–416.

Malone, E. L. (2009). Vulnerability and resilience in the face of climate change: current research and needs for population information. Battelle Memorial Institute, PNWD-4087. Accessible at:

http://www.globalchange.umd.edu/data/publications/Resilience_and_Climate_Change.pdf

Marschke, M., & Berkes, F. (2006). Exploring strategies that build livelihood resilience: a case from Cambodia. *Ecology and Society*, *11*(1).

Marshall, N. A., Marshall, P. A., Tamelander, J., Obura, D., Malleret-King, D., & Cinner, J. E. (2010). A framework for social adaptation to climate change: sustaining tropical coastal communitites [sic] and industries. *International Union of Conservation of Nature (IUCN).* Gland, Switzerland.

Marshall, N., & Marshall, P., (2007). Conceptualizing and operationalizing social resilience within commercial fisheries in northern Australia. *Ecology and society*, 12(1). DOI: https://doi.org/10.5751/es-01940-120101

Marshall, N.A. (2010). Understanding social resilience to climate variability in primary enterprises and industries. *Global Environmental Change* 20.1.: 36-43. DOI: https://doi.org/10.1016/j.gloenvcha.2009.10.003

Maxwell, D., Constas, M., Frankenberger, T., Klaus, D & Mock, M. (2015). Qualitative Data and Subjective Indicators for Resilience Measurement. Resilience Measurement Technical Working Group. Technical Series No. 4. Rome: Food Security Information Network. Available at: http://www.fsincop.net/fileadmin/user_upload/fsin/docs/resources/FSIN_TechnicalSeries_4.pdf

Maxwell, D., Watkins, B., Wheeler, R., & Collins, G. (2003). The coping strategies index: A tool for rapidly measuring food security and the impact of food aid programmes in emergencies. *Nairobi: CARE Eastern and Central Africa Regional Management Unit and the World Food Programme Vulnerability Assessment and Mapping Unit.* Accessible at: http://www.fao.org/3/a-ae513e.pdf

Mayunga, J. (2007) Understanding and Applying the Concept of a Community Disaster Resilience: A capital –based approach. Working paper for the summer academy for social vulner ability and resilience building, 22-28 July 2007. Munich: Germany

McEvoy, D., Fünfgeld, H., & Bosomworth, K. (2013). Resilience and climate change adaptation: the importance of framing. *Planning Practice & Research*, *28*(3), 280-293. DOI: https://doi.org/10.1080/02697459.2013.787710

MEL-CoP. (2016). Analysis of resilience measurement frameworks and approaches. Resilience Measurement, Evidence and Learning Community of Practice. New York: USA.

Miceli R, Sotgiu I, Settanni M. (2008) Disaster preparedness and perception of flood risk: A study in an Alpine Valley in Italy. *Journal of Environmental Psychology*. 28:164–173.

Miller, F., Osbahr, H., Boyd, E., Thomalla, F., Bharwani, S., Ziervogel, G., Walker, B., Birkmann, J., Van der Leeuw, S., Rockström, J. and Hinkel, J. (2010). Resilience and vulnerability: complementary or conflicting concepts?. *Ecology and Society*, 15.3. DOI: https://doi.org/10.5751/es-03378-150311

Mills, M., Mutafoglu, K., Adams, V. M., Archibald, C., Bell, J., & Leon, J. X. (2016). Perceived and projected flood risk and adaptation in coastal Southeast Queensland, Australia. *Climatic change*, *136*(3-4), 523-537. DOI: https://doi.org/10.1007/s10584-016-1644-y

Mishra, S., & Carleton, R. N. (2015). Subjective relative deprivation is associated with poorer physical and mental health. *Social Science & Medicine*, *147*, 144-149.

Mohiyeddini, C., Bauer, S., & Semple, S. (2015). *Neuroticism and stress: The role of displacement behavior*. Anxiety, Stress, & Coping, 28(4), 391-407.

Muffels, R. (2014). Objective and subjective deprivation. *Encyclopedia of Quality of Life and Well-Being Research*, 4409-4413.

Myerson, J., Green, L., & Warusawitharana, M. (2001). Area under the curve as a measure of discounting. *Journal of the experimental analysis of behavior*, 76(2), 235-243.

Nagoda, S. (2015). New discourses but same old development approaches? Climate change adaptation policies, chronic food insecurity and development interventions in northwestern Nepal. *Global Environmental Change*, *35*, 570-579. DOI: https://doi.org/10.1016/j.gloenvcha.2015.08.014

Nelson, D. R. (2011). Adaptation and resilience: responding to a changing climate. *Wiley Interdisciplinary Reviews: Climate Change*, 2(1), 113-120. DOI: https://doi.org/10.1002/wcc.91

Nguyen, K. V., & James, H. (2013). Measuring resilience to floods: A case study in the Vietnamese Mekong River Delta. *Ecology and Society*, **18**, 3–13. https://doi.org/10.5751/es-05427-180313

O'Brien, K. L., & Leichenko, R. M. (2000). Double exposure: assessing the impacts of climate change within the context of economic globalization. *Global environmental change*, *10*(3), 221-232.

O'Sullivan, J. J., Bradford, R. A., Bonaiuto, M., Dominicis, S. D., Rotko, P., Aaltonen, J., ... & Langan, S. J. (2012). Enhancing flood resilience through improved risk communications. *Natural Hazards and Earth System Sciences*, *12*(7), 2271-2282.

O'Brien, G., O'Keefe, P., Gadema, Z. and Swords, J. (2010) 'Approaching disaster management through social learning', Disaster Prevention and Management: An International Journal 19(4): 498–508.

Oddsdóttir, F., Lucas, B., & Combaz, É. (2013). Measuring disaster resilience. *UK: GSDRC University of Birmingham*.

Odum, EP. (1985). Trends expected in stressed ecosystems. *Bioscience* 35:419–422. doi:10.2307/1310021

OECD (2013). *OECD guidelines on measuring subjective well-being*. OECD Publishing. Paris: France. Accessible at: https://www.oecd.org/statistics/oecd-guidelines-on-measuring-subjective-well-being-9789264191655-en.htm

Olsson, L., Jerneck, A., Thoren, H., Persson, J., & O'Byrne, D. (2015). Why resilience is unappealing to social science: Theoretical and empirical investigations of the scientific use of resilience. *Science Advances*, **1**(4), e1400217. https://doi.org/10.1126/sciadv.1400217

Opiyo, F., Wasonga, O., Nyangito, M., Schilling, J., & Munang, R. (2015). Drought adaptation and coping strategies among the Turkana pastoralists of northern Kenya. *International Journal of Disaster Risk Science*, 6(3), 295-309.

Oriangi, G., Albrecht, F., Di Baldassarre, G., Bamutaze, Y., Mukwaya, P. I., Ardö, J., & Pilesjö, P. (2019). Household resilience to climate change hazards in Uganda. *International Journal of Climate Change Strategies and Management.*

Osbahr, H., Twyman, C., Adger, W. N., & Thomas, D. S. (2008). Effective livelihood adaptation to climate change disturbance: scale dimensions of practice in Mozambique. *Geoforum*, 39(6), 1951-1964. doi:10.1016/j.geoforum.2008.07.010

Ostadtaghizadeh, A., Ardalan, A., Paton, D., Jabbari, H., & Khankeh, H. R. (2015). Community disaster resilience: a systematic review on assessment models and tools. *PLoS currents*, 7. DOI: https://doi.org/10.1371/currents.dis.f224ef8efbdfcf1d508dd0de4d8210ed

Paloviita, A., & Järvelä, M. (2015). Climate change adaptation and food supply chain management: an overview. In *Climate Change Adaptation and Food Supply Chain Management* (pp. 19-32). Routledge.

Patel, S. S., Rogers, M. B., Amlôt, R., & Rubin, G. J. (2017). What do we mean by'community resilience'? A systematic literature review of how it is defined in the literature. *PLoS currents*, *9*.

Paton, D. (2003). Disaster preparedness: a social-cognitive perspective. *Disaster Prevention and Management: An International Journal*, 12(3), 210-216.

Pelling, M. (2010). *Adaptation to climate change: from resilience to transformation*. Routledge. Oxford: UK

Pisello, A. L., Rosso, F., Castaldo, V. L., Piselli, C., Fabiani, C., & Cotana, F. (2017). The role of building occupants' education in their resilience to climate-change related events. *Energy and Buildings*, 154, 217-231.doi: https://doi.org/10.1016/j.enbuild.2017.08.024

Platt, S., Brown, D., & Hughes, M. (2016). Measuring resilience and recovery. *International Journal of Disaster Risk Reduction*, *19*, 447-460.

Prior, T., & Eriksen, C. (2013). Wildfire preparedness, community cohesion and social–ecological systems. *Global Environmental Change*, *23*(6), 1575-1586.

Prior, T., & Hagmann, J. (2014). Measuring resilience: methodological and political challenges of a trend security concept. *Journal of risk research*, 17(3), 281-298. DOI: https://doi.org/10.1080/13669877.2013.808686

Pruessner, J. C., Kirschbaum, C., Meinlschmid, G., & Hellhammer, D. H. (2003). Two formulas for computation of the area under the curve represent measures of total hormone concentration versus time-dependent change. *Psychoneuroendocrinology*, 28(7), 916-931.

Raju, E. (2019). Gender as fundamental to climate change adaptation and disaster risk reduction (Chapter 7). *In: Climate Hazards, Disasters, and Gender Ramifications. Eds: Kinnvall, C., & Rydstrom.* H. Routledge: UK.

Renschler, C. S., Frazier, A. E., Arendt, L. A., Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010). A framework for defining and measuring resilience at the community scale: The PEOPLES resilience framework (pp. 10–0006). Buffalo: MCEER.

Roberts, E., Andrei, S., Huq, S., & Flint, L. (2015). Resilience synergies in the post-2015 development agenda. *Nature Climate Change*, 5(12), 1024.

Rohwerder, B. (2016). Seasonal vulnerability and risk calendar in Nepal. Helpdesk Research Report). Applied Knowledge Services. Governance Social Development Humanitarian Conflict. Retrieved March 10, 2017, from http://reliefweb. int/sites/reliefweb. int/files/resources/HDQ1358. pdf.

Rose, A. (2004). Defining and measuring economic resilience to disasters. *Disaster Prevention and Management: An International Journal*, *13*(4), 307-314.

Ruin I, Gaillard JC, Lutoff C. (2007). How to get there? Assessing motorists' flash flood risk perception on daily itineraries. *Environmental Hazards.* 7:235–244.

Schipper ELF., Langston L. (2015). A comparative overview of resilience measurement frameworks: analysing indicators and approaches. ODI Working Paper 422. Overseas Development Institute, London

Schreiner, M. (2012). Simple Poverty Scorecard® Poverty-Assessment Tool Myanmar. Microfinance Risk Management. Accessible at: http://www.simplepovertyscorecard.com/MMR_2009_ENG.pdf

Scolobig A, De Marchi B, Borga M. (2012). The missing link between flood risk awareness and preparedness: Findings from case studies in an Alpine Region. *Natural Hazards.* 63(2):499–520.

Seara T., Clay P M and Colburn L. (2016). Perceived adaptive capacity and natural disasters: A fisheries case study. *Global Environmental Change*,38, 49-57. DOI: https://doi.org/10.1016/j.gloenvcha.2016.01.006

Sherrieb, K., Norris, F. H. and Galea, S. (2010). Measuring capacities for community resilience. *Social Indicators Research,* 99(2): 227–247.

Shumway, R. H., & Stoffer, D. S. (2017). *Time series analysis and its applications: with R examples.* Springer.

Silbert, M., & Useche, M. (2012). *Repeated natural disasters and poverty in Island nations: A decade of evidence from Indonesia.* PURC Working Paper, University of Florida, Department of Economics.

Silva, J. A., & Matyas, C. J. (2014). Relating rainfall patterns to agricultural income: implications for rural development in Mozambique. *Weather, Climate, and Society*, *6*(2), 218-237.

Sjöberg, L. (2000). Factors in risk perception. *Risk analysis*, *20*(1), 1-12.

Slovic, P. (1987). Perception of risk. *Science*, *236*(4799), 280-285.

Smith, B. W., Dalen, J., Wiggins, K., Tooley, E., Christopher, P., & Bernard, J. (2008). The brief resilience scale: assessing the ability to bounce back. *International journal of behavioral medicine*, *15*(3), 194-200. DOI: https://doi.org/10.1080/10705500802222972

Smith, L., Frankenberger, T., Langworthy, B., Martin, S., Spangler, T., Nelson, S., & Downen, J. (2015). Ethiopia pastoralist areas resilience improvement and market expansion (PRIME) project impact evaluation. Baseline survey report. Feed the Future FEEDBACK. Washington, D.C.: United States Agency for International Development.

Sovacool, B. K., D'Agostino, A. L., Rawlani, A., & Meenawat, H. (2012). Improving climate change adaptation in least developed Asia. *Environmental Science & Policy*, *21*, 112-125.

Stuart, E. A., Huskamp, H. A., Duckworth, K., Simmons, J., Song, Z., Chernew, M. E., & Barry, C. L. (2014). Using propensity scores in difference-in-differences models to estimate the effects of a policy change. *Health Services and Outcomes Research Methodology*, *14*(4), 166-182.

Studer, R., & Winkelmann, R. (2014). Reported happiness, fast and slow. *Social indicators research*, *117*(3), 1055-1067.

Sturgess, P. (2016). Measuring Resilience. Evidence on Demand. London: UK. Accessible at: http://www.evidenceondemand.info/measuring-resilience

Sutton, S., & Tobin, R. (2012). Social resilience and commercial fishers' responses to management changes in the Great Barrier Reef Marine Park. *Ecology and Society*, *17*(3). DOI: https://doi.org/10.5751/es-04966-170306

Swim, J. K., Clayton, S., & Howard, G. S. (2011). Human behavioral contributions to climate change: Psychological and contextual drivers. *American Psychologist*, *66*(4), 251.

Sylvestre, N., Brutus, N., Mishell, C. et al. (2012). Haiti Humanitarian Assistance Evaluation From a Resilience Perspective. Tulane University's Disaster Resilience Leadership Academy in Collaboration with State University of Haiti. New Orleans: USA. Accessible at: http://www2.tulane.edu/drla/upload/UEH-Tulane-DRLA-Haiti-Humanitarian-Aid-Evaluation-ENGLISH-May-2012.pdf

Tanner, T., Lewis, D., Wrathall, D., Bronen, R., Cradock-Henry, N., Huq, S., ... & Alaniz, R. (2015). Livelihood resilience in the face of climate change. *Nature Climate Change*, 5(1), 23.

Thomalla, F., & Larsen, R. K. (2010). Resilience in the context of tsunami early warning systems and community disaster preparedness in the Indian Ocean region. *Environmental Hazards*, *9*(3), 249-265.

Tiberius, V. (2006). Well-Being: Psychological Research for Philosophers. *Philosophy Compass*, *1*(5), 493-505. DOI: https://doi.org/10.1111/j.1747-9991.2006.00038.x

Tiwari, S., E. Skoufias, and M. Sherpa. (2013). Shorter, Cheaper, Quicker, Better: Linking Measures of Household Food Security to Nutritional Outcomes in Bangladesh, Nepal, Pakistan, Uganda, and Tanzania. The World Bank. Washington, DC: USA.

Todman, L. C., Fraser, F. C., Corstanje, R., Deeks, L. K., Harris, J. A., Pawlett, M., ... & Whitmore, A. P. (2016). Defining and quantifying the resilience of responses to disturbance: a conceptual and modelling approach from soil science. *Scientific reports*, 6, 28426.

Toole S, Klocker N, Head L (2016) Re-thinking climate change adaptation and capacities at the household scale. Climatic Change 135(2):203–209. doi: 10.1007/s10584-015-1577-x

Tschakert, P., & Dietrich, K. A. (2010). Anticipatory learning for climate change adaptation and resilience. *Ecology and society*, 15(2).

Tuler, S., Agyeman, J., Agyeman, J., da Silva, P. P., LoRusso, K. R., & Kay, R. (2008). Assessing vulnerabilities: Integrating information about driving forces that affect risks and resilience in fishing communities. *Human Ecology Review*, 171-184.

Twigg J. (2009)., Characteristics of a disaster-resilient community: a guidance note. version 2. London: University College London.

Tyler, S., & Moench, M. (2012). A framework for urban climate resilience. *Climate and development*, *4*(4), 311-326.

Ungar, M. (2008). Resilience across cultures. The British Journal of Social Work, 38(2), 218-235.

United Nations. (2015a). Transforming our world: The 2030 agenda for sustainable development. United Nations. USA: Washing D.C.: USA

United Nations. (2015b). Adoption of the Paris Agreement. United Nations Framework Convention on Climate Change. Paris: France.

Vaitla, B., Tesfay, G., Rounseville, M., & Maxwell, D. (2012). Resilience and livelihoods change in Tigray, Ethiopia.: Tufts University Feinstein International Center. Somerville: USA.

Vincent, K. (2007). Uncertainty in adaptive capacity and the importance of scale. *Global Environmental Change*, 17(1), 12-24. DOI: https://doi.org/10.1016/j.gloenvcha.2006.11.009

Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The risk perception paradox—implications for governance and communication of natural hazards. *Risk analysis*, 33(6), 1049-1065.

Walker, B., Holling, C. S., Carpenter, S. R., & Kinzig, A. (2004). Resilience, adaptability and transformability in social–ecological systems. *Ecology and society*, *9*(2).

Walker, BH., Ludwig, D., Holling, CS., Peterman RM. (1981). Stability of semi-arid savanna grazing systems. *Journal of Ecology*. 69.2.:473–498. doi:10.2307/2259679

Waller, M. A. (2001). Resilience in ecosystemic context: Evolution of the concept. *American Journal of Orthopsychiatry*, *71*(3), 290-297.

Waters, J., & Adger, W. N. (2017). Spatial, network and temporal dimensions of the determinants of adaptive capacity in poor urban areas. *Global Environmental Change*, 46, 42-49. DOI: https://doi.org/10.1016/j.gloenvcha.2017.06.011

Weber, E. U. (2010). What shapes perceptions of climate change? *Wiley Interdisciplinary Reviews: Climate Change,* 1(3), 332-342. DOI: https://doi.org/10.1002/wcc.41

Wheeler, Andrew P. "Tables and graphs for monitoring temporal crime trends: Translating theory into practical crime analysis advice." *International Journal of Police Science & Management* 18.3 (2016): 159-172.

Windle, G., Bennett, K. M., & Noyes, J. (2011). *A methodological review of resilience measurement scales. Health and quality of life outcomes*, 9(1), 8.

Wineman, A., Mason, N. M., Ochieng, J., & Kirimi, L. (2017). Weather extremes and household welfare in rural Kenya. *Food security*, *9*(2), 281-300.

Wooldridge, J. M. (2016). *Introductory econometrics: A modern approach*. Nelson Education.

World Bank. (2017). An analysis of poverty in Myanmar: part one - trends between 2004/05 and 2015 (Vol. 2) (English). USA: Washington D.C. Available at: http://documents.worldbank.org/curated/en/556581502987486978/An-analysis-of-poverty-in-Myanmar-part-one-trends-between-2004-05-and-2015

Wring, D., Mortimore, R., & Atkinson, S. (Eds.). (2018). *Political Communication in Britain: Campaigning, Media and Polling in the 2017 General Election*. Springer.

Yaro, R. (2019). Résilience des agriculteurs face aux changements climatiques: un exemple d'application au Burkina Faso. MSc Thesis. Université Laval. Quebec: Canada

Yaron, G., Wilson, D., Dumble, S., Murphy, B. (2017). Measuring changes in household resilience as a result of BRACED activities in Myanmar. Building Resilience and Adaptation to Climate Extremes and Disasters (BRACED). London: UK.

Zhou, H., Wan, J., & Jia, H. (2010). Resilience to natural hazards: a geographic perspective. *Natural hazards*, *53*(1), 21-41.

Zobel, C. W. (2014). Quantitatively representing nonlinear disaster recovery. *Decision Sciences*, 45(6), 1053-1082.

Zobel, C. W., & Khansa, L. (2014). Characterizing multi-event disaster resilience. *Computers & Operations Research*, *42*, 83-94.