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November 2018

Centre for Climate Change Economics and Policy Working Paper No. 342
ISSN 2515-5709 (Online)

Grantham Research Institute on Climate Change and the Environment Working Paper No. 308
ISSN 2515-5717 (Online)

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Suggested citation:
Clare A, Sagynbekova L, Singer G, Bene B and 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

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This working paper is intended to stimulate discussion within the research community and among users of research, and its content may have been submitted for publication in academic journals. It has been reviewed by at least one internal referee before publication. The research for this paper was carried out as part of the PRISE project, under the Collaborative Adaptation Research Initiative in Africa and Asia (CARIAA), with financial support from the UK Government's Department for International Development (DfID) and the International Development Research Centre (IDRC), Canada. The views expressed in this paper are those of the authors and do not necessarily represent those of the host institutions and its funders, including DfID and IDRC or its Board of Governors.

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Declarations of interest: none

Acknowledgements

This work is associated to the Collaborative Adaptation Research Initiative in Africa and Asia (CARIAA) with financial support from the UK Government's Department for International Development and the International Development Research Centre, Ottawa, Canada. The views expressed in this work are those of the creators and do not necessarily represent those of the UK Government's Department for International Development, the International Development Research Centre, Canada or its Board of Governors. Financial support from the Grantham Foundation for the Protection of the Environment, and the UK Economic and Social Research Council (ESRC) through the Centre for Climate Change Economics and Policy is also acknowledged. We are grateful to Lindsey Jones, Sam Fankhauser and Declan Conway for their helpful comments.

ABSTRACT

Recent attempts to develop a standardised tool to quantify levels of household resilience to climate extremes typically generate very large household surveys, which take a number of hours to complete. Moreover significant questions exist around which resilience capacities to measure, how to measure them, and how to weight them for their relative importance in facilitating or hindering resilience in any given context. Subjective approaches to resilience measurement may offer an attractive alternative, because they ask respondents for a rating of their overall perceived resilience, thereby placing more emphasis on what resilience means to local people and leaving the choice of which capacities, in what combination and quantities up to them. This paper is the first to quantitatively compare the power of subjective and objective resilience measures to predict future wellbeing (in this case, represented by household food security) in the face of socio-environmental shocks and stressors. Using a household panel data set collected in three contrasting rural Kyrgyzstan villages, our results reveal that subjective resilience indicators are strong independent predictors of future food security. The subjective indicators capture variance that is not picked up by standard objective indicators and significantly increase the accuracy of models that predict future levels of household food security. Moreover there is tentative evidence that the subjective resilience indicators developed in this study may be comparable across contexts, however more research is required to confirm this early-stage observation.

KEYWORDS

Resilience; Subjective; Objective; Measurement; Climate change; Food security

INTRODUCTION

It is increasingly clear that the impacts of climate change will be experienced in part as an intensification of the frequency and severity of climate-related extreme events (Fields 2012), and moreover that the impacts of these events will be felt most severely by the world's most vulnerable communities (Hallegatte et al. 2016; IPCC 2014). As a result, a significant portion of development programming activities, specifically those falling within the remits of climate adaptation (CA) and disaster risk reduction (DRR), is now focused on building resilience to such events (Bahadur et al. 2010).

Conceptually resilience is not new and has previously been defined and studied across a wide range of disciplines including ecology, engineering, communities and psychology (Alexander 2013; Quinlan et al. 2016). Each of these disciplines emphasises different characteristics of what a resilient system looks like. For example, engineering resilience focuses on the speed with which a system can return to equilibrium after a shock, thus emphasising efficiency of recovery processes within a relatively simple system. In contrast, ecological resilience takes a more systemic perspective, stating that *"resilience determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist''* (p. 17; Holling 1973). Taking a similarly broad and dynamic view is psychological resilience, which studies the importance and influence of interacting and dynamic psychosocial processes that strongly influence an individual's ability to cope with and adapt to traumatic life events (Graber et al. 2015).

Applications of resilience theory to CA and DRR typically use a socio-ecological systems approach that emphasises adaptive capacity, learning and innovation (Carpenter et al. 2001; Nelson et al. 2007; Brown & Westaway 2011), and/or a development resilience approach. The latter focuses on the capacity of a person or household to maintain a certain level or stay above a specified threshold of wellbeing indicators such as poverty (Barrett & Constas 2014; Jennifer & Barrett 2016) and/or food security (D'Errico, Pietrelli, et al. 2016; Upton et al. 2016; Ciani 2013) in the face of shocks and stressors. In this context, resilience tends to be seen as a combination of capacities '*that ensures adverse stressors and shocks do not have long-lasting adverse development consequences'* (p.6, Constas et al. 2014). As such, a certain state of resilience is not the goal in and of itself, but rather is an interim step that is assumed will lead to better wellbeing outcomes over time for the individual, household and/or community in question (Constas, TR Frankenberger, Hoddinott, et al. 2014; Constas, TR Frankenberger & Hoddinott 2014).

There is now great interest in the development of standardised resilience metrics in line with the growing application of resilience theory to CA and DRR activities, and ideally they should have two key features. Firstly, they should be valid and reliable predictors of future wellbeing (as measured by specified indicators such as poverty and food security), because resilience is theorised as a combination of capacities that facilitates a future state of wellbeing. Secondly, resilience metrics should be comparable across space, both within a specific context (i.e., resilience levels of two households in the same community) and preferably across contexts (i.e., resilience levels of two households in different communities). Combined together, these characteristics of wellbeing prediction and cross-context comparability would allow CA and DRR programme activities to be targeted to the least resilient communities.

Resilience metrics that are predictive and comparable

There have been many attempts to develop a predictive and comparable resilience metric, and they have tended to follow a similar methodology. Acknowledging that resilience is a multi-faceted set of capacities existing across many systemic levels (e.g., individual, community, national), the typical approach is to identify all possible resilience capacities at all levels and then to assign each of those capacities with a quantitative indicator. This indicator either measures the resilience capacity directly (e.g., in the case of asset values) or indirectly using a proxy variable (e.g., using the number of social groups of which a respondent is a member as an indication of the strength of their social networks). These quantified resilience capacities are then generally combined into a single metric using a range of possible techniques varying from simple averaging to more advanced techniques like principal components analysis (e.g., Ciani 2013; D'Errico, Garbero, et al. 2016).

However there are many well-known criticisms of this approach. Firstly there is significant contention over which resilience capacities should be chosen and which indicators to choose in order to accurately represent those capacities. Moreover there is a high likelihood that the capacities that are deemed easier to quantify (e.g., basic socio-demographics, wealth and existence of physical protection structures such as flood defences) will be included more often than less tangible elements that may be incompatible with quantification (e.g., local power dynamics and corruption). This risks the former becoming the dominant narrative for the drivers of resilience simply by virtue of relative measurement ease, when it may actually be the latter dimensions that are the most important determinants of coping with and adapting to shocks and stressors (Levine 2014; Brown 2014).

In addition to choosing meaningful indicators to represent resilience capacities, there is also concern over how to interpret the values of these indicators. For example, there are notable cases where even having assets of a relatively high value has negative impacts (Lautze & Raven-Roberts 2006; Young et al. 2009). Moreover many of the capacities that these indicators aim to represent will interact with each other in dynamic cycles that may impact on wellbeing only when they reach certain thresholds (Béné et al. 2011; Levine 2014; Barrett & Constas 2014).

One of the most systematic attempts to develop a standardised quantitative resilience metric is FAO's RIMA-II (FAO 2016), which uses factor analysis to formulate a Resilience Capacity Index (RCI) and then tests its capacity to predict a wellbeing outcome of interest, which is typically a measure of food security and/or poverty. There is some evidence that this approach has predictive power for food security (Ciani 2013), however the question remains as to whether the intense methodological complexity of deconstructing, quantifying and then reconstructing resilience in this way is the most effective and efficient methodology possible for the task of estimating the resilience level of a household. In fact, there is growing interest in the idea that subjective approaches to resilience measurement may be able to add value by predicting future wellbeing in the face of shocks and stressors, using a much shorter questionnaire, and perhaps even providing standardised resilience comparisons across differing contexts (Clare et al. 2017; Béné et al. 2016; Jones & Tanner 2016). The following section summarises the application of subjective approaches to the development of standardised metrics in other fields and reviews their application to date in the fields of CA and DRR.

Using subjective approaches to develop resilience metrics

Subjective measures are those that seek to elicit opinion, perceptions and/or preferences from individuals, rather than observable or verifiable data such as events, behaviours or material conditions (Maxwell et al. 2015). These latter data types are often called objective measures and make up the vast majority of indicators included in most resilient assessment tools (FAO 2016; Constas, T.R. Frankenberger, Hoddinott, et al. 2014; UNDP 2014) Although there is a continuum between subjective and objective measures, a good rule of thumb is that the answers to subjective questions cannot be externally verified or observed. For example, although it is possible to verify a household's wealth or livestock herd value to some extent, it is impossible to objectively prove the strength of someone's opinion or the validity of their perception. The validity of their opinion at a given time is implicit in their action of expressing it.

Importantly a distinction is drawn here between the subjectivity implicit in qualitative methods that produce narratives and prose structures of data as compared to the development of quantified subjective metrics, which are designed to assign a numerical value to a person's subjective appraisal of their situation through, for instance, the use of Likert-scale techniques. It is this latter application of subjective approaches that is of interest here to the development of a predictive and comparable resilience metric.

Subjective approaches have been used for many decades to develop metrics in research fields that try to access information on intangible concepts, most notably in studies of wellbeing and psychological resilience (Diener et al. 1985; Oishi et al. 1999; Ungar & Liebenberg 2011; Liebenberg & Moore 2016; Kahneman & Krueger 2006). For example, the Satisfaction With Life Scale is a well-known measure of subjective wellbeing, developed by Diener et al. (1985) and consisting of five statements (for example, "In most ways my life is close to ideal") with which respondents are asked to rate their agreement on a seven-point Likert scale from 1 (Strongly disagree) to 7 (Strongly agree). This scale has been used in a large number of countries worldwide, with interesting relationships to the traditional objective measures of wellbeing such as income and material wealth (Camfield et al. 2010; Oishi et al. 1999; Balatsky & Diener 1993). Additionally there are many standardised scales of psychological resilience in existence, all aiming to quantify respondents' perceptions and/or opinions with respect to their ability to 'bounce back' and deal with the various challenges that they experience during their lifetimes (Windle et al. 2011; Liebenberg et al. 2013; Connor & Davidson 2003).

More recently subjective approaches have been gaining momentum within the CA and DRR resilience fields, having notably been included in the Food Security Information Network's comprehensive resilience measurement principles (Maxwell et al. 2015) and trialled in various formats to develop resilience and/or adaptive capacity metrics in context-specific studies around the world (Marshall & Marshall 2007; Lockwood et al. 2015; Seara et al. 2016; Nguyen & James 2013).

These subjective approaches may address some of the draw-backs of objective approaches on a number of dimensions. Firstly, by asking the respondents for their perspective on how well they are able to maintain their wellbeing in the face of shocks and stressors, subjective approaches avoid the need to identify and choose which resilience capacities may or may not be relevant to them in that given time and place, and are not then tasked with finding appropriate indicators that are expected to represent these capacities effectively. Moreover the interpretation of the level of each of those indicators, whether they are close to critical thresholds, and which other capacities they may be interacting with remains within the mind of the respondents. In effect, a subjective resilience question/series of questions should facilitate an internal RIMA-style process within a respondents' mind, stimulating them to consider carefully each of their capacities, levels, and interactions, and then asking them to rate their confidence in those capacities to assist them in maintaining a certain level of wellbeing over time. In this way, a subjective approach assumes that the respondents are the best placed individuals to know which resources they need, in what quantity, and how these resources interact with each other to help or hinder their own ability to maintain their wellbeing under certain circumstances.

Importantly, this process does not tell us which capacities, and in what quantity, are most important to the respondent, and therefore is not recommended for in-depth assessments that aim to elucidate and understand the underlying drivers of resilience in order to design policies and programmes. However, we argue that this subjective approach does have potential in contributing to the search for a standardised and quantified index of resilience that can predict wellbeing in the future and perhaps may even be comparable across contexts (Clare et al. 2017).

A small number of studies have developed and investigated quantitative subjective resilience measures (Béné et al. 2016; Jones et al. 2018; Lockwood et al. 2015; Nguyen & James 2013), however none of them have tested their predictive power for future wellbeing or their comparability across space. Firstly, most of the CA/DRR studies using quantitative subjective measures developed questions that are specific to the context of the single case study within which they were working. For example, Nguyen & James (2013) developed statements about flood resilience for Vietnamese rice farmers such as *"I am confident that my household has enough rice to eat during flood season"* and ask respondents to rate their agreement with them. Similarly, Lockwood et al. (2015) ask rural Australian landholders to rate their agreement with statements that were developed to measure dimensions of adaptive capacity such as social capital *("As a result of building connections with local groups I better understand how my conservation management contributes to the Tasmanian and Australian communities")* and trust in government ("*As a result of building connections with local groups I have more trust in people from government agencies*"). The context specificity of these statements is important to ensure the relevance of the analysis, but it also means that these measures may not be applicable outside the local situation in which they were developed. As such they do not meet the demand for standardised resilience metrics that are comparable across space.

Some other studies have proposed a more generic or standardised metric that can be applied across locations. For example, Béné et al. (2016) studied the resilience of fishing communities in Ghana, Sri Lanka, Fiji and Vietnam using four standardised questions displayed in Figure 1.

Figure 1 – Standardised subjective resilience questions used by Bene et al. 2016

1. Recovery from past event:	
With respect to [EVENT], how well do you consider you managed to recover?	Not at all and I don't think I will be able to recover = 1 Not yet fully recovered and it will be difficult/long = 2 Not yet but hope very soon = 3 Have fully recovered –but it was long and painful = 4 Have fully recovered –and it was not too difficult = 5 Have fully recovered and I am better off now = 6
2. Relative recovery from past event: With respect to [EVENT], how well do you consider you did, compared to the rest of the community?	Did worse than most of the others = 1 As bad as some people but better than others = 2 Like most of the others = 3 Did better than most of the others = 4 Did better than anyone else = 5
3. Community recovery from past event: With respect to [SHOCK NAME], how well do you consider the community recovered:	Not at all and I don't think we will be able to recover = 1 Not yet fully recovered and it will be difficult/long = 2 Not yet but hopefully very soon = 3 Have fully recovered –but it was long and painful = 4 Have fully recovered –and it was not too difficult = 5 Have fully recovered and we are now better off = 6
4. Capacity to handle future event: With respect to [EVENT], if it was to happen again in the near future how do you consider you would be able to recover?	Would be worse than last time = 1 As bad as last time = 2 More or less the same than last time = 3 As well as last time = 4? Would do better than last time = 5

This study found that people's perceptions of their own resilience (represented by answers to the questions listed in Fig 1) were strongly correlated with the severity of shocks that they had experienced and the extent to which shocks had disrupted their income, but resilience was not significantly correlated with the predictability and type of the events experienced.

However, despite providing comparative data across contexts, this study only collected data in one time period and therefore could not test the ability of subjective resilience measures to predict future wellbeing. Therefore there has been no study to date that has tested both the potential of subjective resilience measures to predict future wellbeing and then rested the measures' validity and reliability across different contexts.

The present study was therefore designed to address this knowledge gap, using food security as the wellbeing outcome of interest. Building on previous questions about the potential value-added of subjective resilience measures (Clare et al. 2017), this research asks the following questions:

- Are subjective resilience measures significant predictors of future food security?
- Can they be used to reduce the questionnaire burden on respondents?
- Are subjective resilience measures directly comparable across contexts?

We address these questions by collecting and analysing panel household survey data from three rural communities in Kyrgyzstan, Central Asia.

MATERIAL AND METHODS

Background information on Kyrgyzstan

Kyrgyzstan is one of five Central Asian countries, linked both through their geographical location and shared history as part of the Soviet Union. Kyrgyzstan suffered significant economic and agricultural productivity decline following independence in 1991, and its subsequent transition from a state-driven to a market-oriented economy. In recent years it has recorded modest but stable growth and is led by a democratic government, however significant social problems still exist. For instance, a national poverty headcount of 32.1% (World Bank 2015) with regional disparities reaching 50% in some rural areas compared to 18% in the capital, Bishkek (Atamanov 2013).

The extent of rural poverty in Kyrgyzstan is particularly pertinent in light of the country's vulnerability to climate change. Central Asia is predicted to be severely impacted by climate change impacts under a 2 degree scenario, with projections suggesting temperatures increasing by up to 6.5 degrees above pre-industrial temperatures by the end of this century (Reyer et al. 2017). Moreover Kyrgyzstan is ranked as the third most vulnerable country to climate change impacts within 28 countries from Eastern Europe and Central Asia, predominantly due to the sensitivity of its agricultural systems to climatic change and its very low adaptive capacity (ranked 24th of the 28 countries; Fay et al. 2010).

The impacts of climatic temperature changes will most likely be experienced through altered precipitation patterns and more frequent heat extremes, leading to increased incidence of aridity and drought, particularly in the mountain pastures. Moreover Kyrgyzstan's land area is 90% mountainous and therefore increasing temperatures may quicken snow and glacial melt, leading to an increased frequency and intensity of floods and mudflows (Ilyasov et al. 2013). In fact there is already an observable trend of increases in extreme weather events since 1990 *(ibid).* As such, Kyrgyzstan's rural exposure, sensitivity and relative lack of adaptive capacity to climate-related shocks and stressors make it a natural choice within which to develop and test standardised subjective resilience measures.

Selection of case-study villages

Longitudinal surveys were conducted in three Kyrgyz villages, spanning three oblasts (Kyrgyz provinces): Naryn, Batken and Jalal-Abad. These oblasts were chosen to represent a geographical and socio-environmental range of livelihood types in Kyrgyzstan (see Table 1). One village within each oblast was chosen based on the following characteristics:

- Semi-aridity: this research was conducted as part of the PRISE project (Pathways to Resilience in Semi-Arid Economies: www.prise.odi.org), focusing on the resilience pathways of semi-arid regions across the world. The classification of semi-aridity was based on the Köppen-Geiger classification (Climate-data.org 2018)
- Population size: the target village size was 400 or more households, to ensure that our sample size of 200 households per location could be met
- Year-round accessibility: the survey needed to run through winter therefore year-round accessibility by car was necessary to transport the survey team to and from the locations
- Food insecurity: food insecurity was the main outcome measure used in the survey, therefore areas which were known to have experienced significant food insecurity were prioritised. This information was discerned from discussions with local partners and existing reports (World Food Programme 2014).
- Likelihood of climate-linked shocks and stressors: the purpose of the study was to investigate the impact of climate-related shock/stressor events on the resilience and wellbeing of households, therefore villages with past experience of such shocks and stressors were identified through conversations with local partners.

An initial shortlist of 15 villages was drawn up and then progressively narrowed down through iterative meetings between the project team and a range of NGO representatives. The characteristics of the three final selected villages are provided in Table 1.

Table 1: Selection characteristics of the three case study villages

Province	District	Village	No. of HHs	Population	Nearest town centre (km)	Altitude (m)	Agricultural activities
Naryn	Naryn	8 Mart	500	2493	70	2039	Livestock husbandry, fodder crops, some vegetables
Jalal-Abad	Bazar-Korgon	Kyzyl-Ai	990	4965	5	680	Arable crops vegetables, some livestock
Batken	Batken	Chet-Kyzyl	561	2600	15	1000	Apricot orchards, arable, some livestock

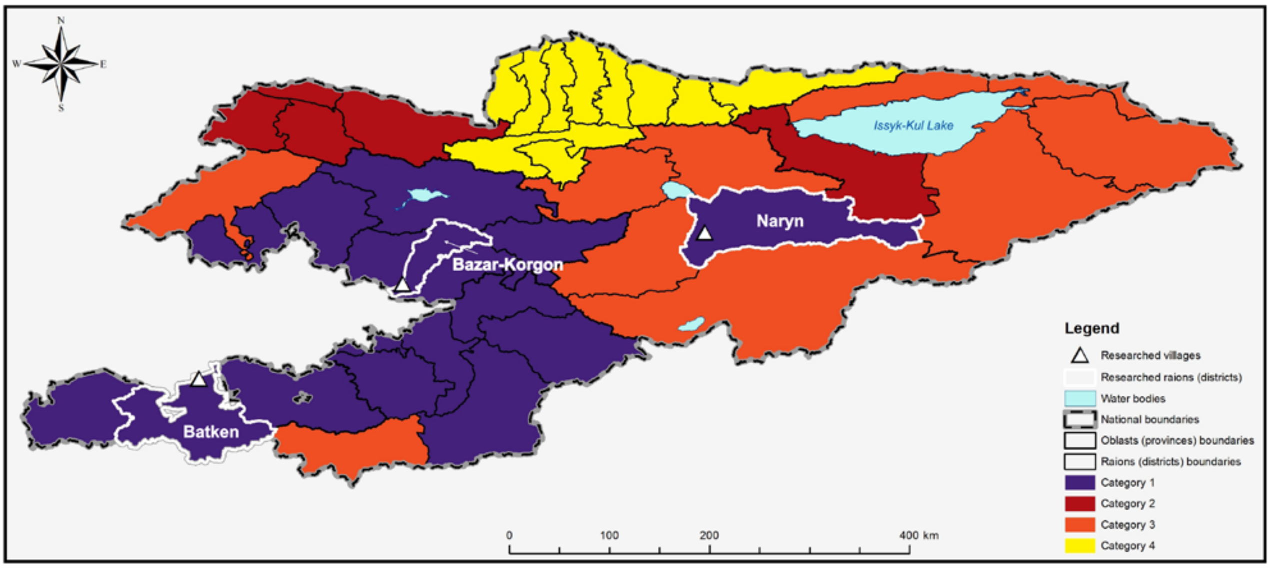
Figure 2 displays the geographical location of the villages using a map adapted from a World Food Programme (2014a) report that overlaid data on the recurrence of poverty and exposure to shocks. The figure clearly shows that all three villages are located in 'Category 1' districts, which were defined as experiencing high recurrences of poverty and high or medium risk of natural shocks, relative to the rest of the country.

Setting up the longitudinal surveys

A questionnaire survey of closed-ended questions was developed on the basis of data collected during a series of 16 focus group sessions spread across the three locations (see Appendix A for more details), combined with a literature review on measurement of resilience, wellbeing and food-security. The questionnaire was translated from English to Kyrgyz by two project team members, and then back translated by a third to ensure accuracy of question meaning. Surveys were delivered using electronic tablets and Open Data Kit (ODK) software. Three teams of 4-5 surveyors plus one team leader were recruited and trained in each location. These teams were re-trained and more surveyors added if needed before each successive round.

Surveys were completed at each location in April, July and November 2017, starting before and then continuing to monitor households throughout the main shock/stressor risk windows and critical periods for agricultural activities. These risk windows and critical periods included: floods, mudslides, & planting crops in May/June, droughts, livestock and crop disease in June/July, and financial stressors from social events and weddings which traditionally occur in the months of August and September. Appendix B provides detailed information on sampling strategy and questionnaire content.

Figure 2: WFP graphic mapping combined indices for poverty and exposure to natural shocks



Outcome measure: the HFIAS

Food insecurity was measured using the Household Food Insecurity Access Scale (HFIAS), which is one of many indices developed in recent years to assess one or more of the pillars of food security: availability, access, utilisation and risk (Maxwell et al. 2013). Similar to resilience, food security is a complex, multi-dimensional concept that can be difficult to capture quantitatively. Initial measurement attempts focused on age-adjusted per-capita calorie intake and anthropometric indicators of nutritional status. However, in addition to being technically challenging and highly data intensive (Coates et al. 2007) these measures were also criticised for having dubious nutritional relevance, poor inter-temporal validity and questionable sensitivity to the negative impacts of shocks and stressors on household wellbeing (Headey & Ecker 2013). As a result, a series of less data intensive indicators have been developed to measure food insecurity, including the Food Consumption Score (FCS), the Household Dietary Diversity Score (HDDS), the Household Hunger Scale (HHS) and the HFIAS. Comparative analysis between these indicators suggest that the HFIAS is well correlated with other food security scales, despite each index seeming to capture slightly different elements of the overall food security picture (Maxwell et al. 2013). The HFIAS specifically seems to measure a mix of food sufficiency and psychological factors *(ibid)* and this scale was chosen as the outcome indicator for this paper due to the overall interest in comparisons between objective and subjective measurement approaches.

Measurement of subjective resilience

This study developed two new metrics for subjective resilience: one generalised and one shock-specific. The shock-specific measure was developed because there is general consensus within the climate resilience literature that resilience should be defined in relation to specified events. For example, a household's resilience to a flood may be very different to its resilience to a drought (Choularton et al. 2015). However we also developed a generalised measure of subjective resilience, based around the respondent's understanding of how they are able to maintain their wellbeing to shocks and stressors that they experience regularly, or in a 'typical' year, as compared to the impacts of larger or less common shocks and stressors that they might experience in a 'bad' year. Both the question and response structures were formulated from the focus group sessions that took place in each location. The sub-sections below provide more detail on the development processes for the two subjective resilience questions.

Generalised measure of subjective resilience

Respondents were asked to identify shocks and stressors they would expect to experience in a 'typical' year from a locally relevant list. They were then asked the question, "In a year where you experience the events that you just chose, i.e., a typical year, how is your family's wellbeing?" and could choose from six responses:

- We are always fine, regardless of these events
- We are mostly fine, and almost always have enough food and money
- Sometimes we struggle to have enough but we mostly get through
- It is difficult to find enough food and money for our needs
- It is really difficult to find enough food and money for our needs
- We are unable to meet even our basic needs for surviving

This question was then repeated with the emphasis on the shocks/stressors experienced and subsequent impact on wellbeing in a 'bad' year. This generated two scores for generalised resilience: one for a typical year and one for a bad year.

Shock-specific measure of subjective resilience

In each survey wave respondents were asked to choose three options from a list of locally relevant shocks whose occurrence they were most concerned about in the coming 3-4 months (the approximate time gap between survey rounds). For each event chosen they were asked, "If [EVENT] happens in the next 3-4 months, how do you think it will affect your family's wellbeing?" and could choose from six responses:

- We will be totally fine
- We will mostly be fine, and almost always have enough food and money
- We might struggle a bit but we'll get through
- It will be difficult to find enough food and money for our needs
- It will be really difficult to find enough food and money for our needs
- We will be unable to meet our basic needs for surviving

Both of these measures intentionally avoid breaking resilience down into subsets of characteristics and simply seek to test the predictive power of these subjective assessments of a family's ability to maintain their wellbeing under 'typical' and 'bad' scenario years, and in relation to specific shocks that they are particularly concerned about.

RESULTS

Descriptive results

Overview of community level characteristics

Over 200 households were interviewed in each community at baseline, and household retention rates were high in all locations (89% or above). As subjective questions tap into an individual's perception, surveyors were instructed to interview the same person within the household wherever possible in order to maintain consistency of subjective viewpoints across time. Finding the same respondent in each household can be difficult, however the same person was interviewed for all three rounds in 72% - 99% of households (see Table 2).

Surveyors were instructed to request an interview with the most senior household member available at the time, and interestingly there were relatively high numbers of female respondents, ranging from 46% in Naryn to 61% in Batken. The higher numbers in Batken and Jalalabad likely reflects the higher external migration rates of males in these communities, creating more female-headed households.

Table 2: Community level socio-demographic characteristics

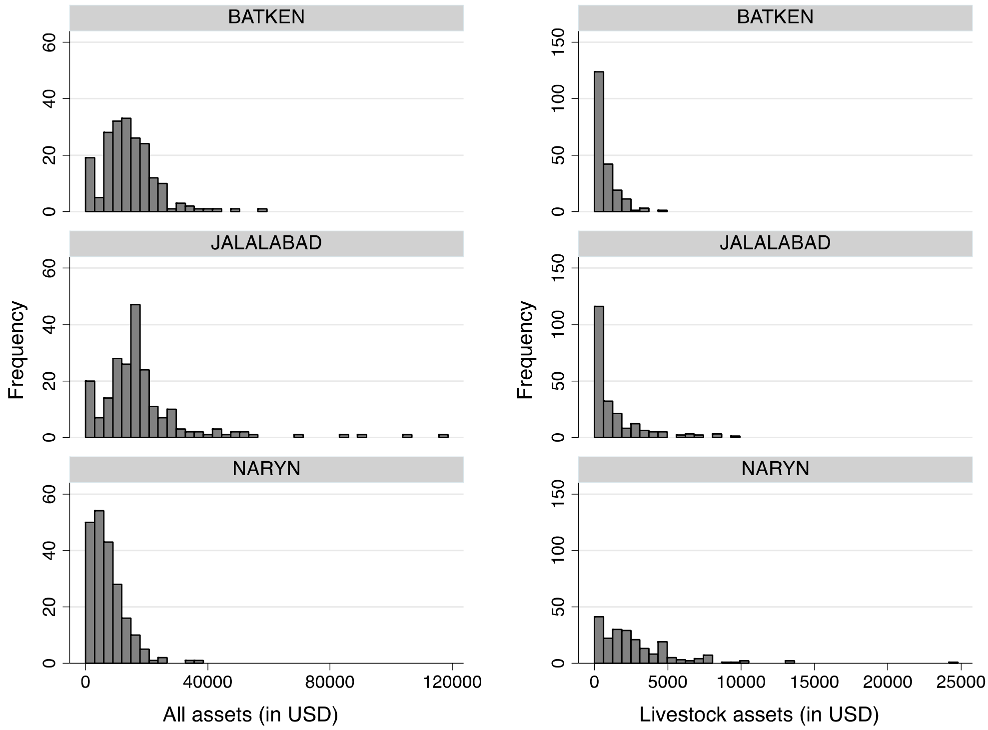
	Batken	Jalalabad	Naryn
Number of respondents	201	216	211
HH retention rate across all survey waves (%)	100%	96%	89%
Respondent (and HH) retention rate across all survey waves (%)	99%	78%	72%
Female respondents (%)	61	56	46
Average number of adults (>16yrs) per HH*	3.2	3.9	3.1
Average number of children (<16yrs) per HH*	2.9	2.3	2.5
Adult to child ratio*	1.10	1.70	1.24
Average number of adults receiving pensions per HH*	0.32	0.48	0.91
% adults (>=18yrs) migrating externally*	6.6%	20.1%	3.6%
% adults (>=18yrs) migrating internally*	4.0%	1.8%	6.4%
Mean household wealth USD (all sources)*	15,677	18,015	7,218
Median household wealth USD (all sources)*	14,042	15,491	6,216
Mean household wealth USD (livestock)*	664	1,249	2,811
Median household wealth USD (livestock)*	490	490	2,030

* - Statistically significant difference at p<0.05

Means comparison using ANOVA with James' correction (allowing for heterogeneous covariances across locations) revealed significant differences across locations in the demographic structures, migration patterns, and wealth of surveyed households. Most of the indicators displayed in Table 2 revealed significant differences between locations (as denoted by an asterisk), suggesting that the goal to work in villages with different socio-demographic characteristics was met.

Household wealth was calculated by asking what value households felt they could obtain for a variety of asset types (listed above in the 'Survey Content' section) if they were to sell them at that point in time. The value of all these assets was then summed to provide an estimate of household wealth. From Table 2 and Figure 3 there is a clear pattern of wealth differences between the three communities, both in the quantity and type of assets. Jalalabad and Batken residents have total assets of significantly higher value than in Naryn, and less than 10% of this asset value is contained in livestock, with the majority coming from possessions such as cars, agricultural machinery, fridges, TVs, owned houses and land. In contrast, Naryn residents have on average less than half the total wealth of residents in Batken and Jalalabad, and they typically hold over 30% of this wealth in the value of their livestock.

Figure 3: Total and livestock-only assets frequency distribution by community



The percentage of adults migrating externally (defined as migration outside of Kyrgyzstan and most commonly referring to the migration of Kyrgyz men to Russia in search of jobs) is much higher in Jalalabad (20.1%) than in Batken (6.6%) or Naryn (3.6%). Intuitively this follows the pattern of wealth distribution, with the poorest community (Naryn) sending the fewest family members to work abroad due to the significant investments required for travel and relocation.

In contrast, internal migration within Kyrgyzstan rates are highest in Naryn (6.4%) and lowest in Jalalabad (1.8%). Notably, Naryn is the only location where internal migration rates are higher than external migration rates. These results fit with discussion in the focus groups which revealed that internal migration was an undesirable way to earn a living, as jobs within Kyrgyzstan tend to offer very low wages compared to those outside the country, and therefore people were far less willing to leave their families for prolonged periods. Therefore only those who had few other means of earning money would consider internal migration as an option. This focus group observation is supported by a regression of logged assets on internal and external migration, which shows a significant positive correlation with external (p-value=0.02) and a negative (but insignificant) correlation with internal migration (p-value=0.43), controlling for community fixed effects.

Food security and wellbeing

As the wealthiest community, Jalalabad consistently reports the highest food security as measured by the HFIAS instrument, with 5.1% of respondents reporting daily/often food quality shortages, and just 1.4% reporting daily/often food quantity shortages. On the other hand, despite the significantly higher average wealth of Batken residents compared to Naryn residents, Batken residents report consistently lower food security scores at baseline, with 31.8% versus 22.3% reporting often/daily food quality shortages, and 9.5% versus 2.4% reporting often/daily food quantity shortages. This pattern of Batken reporting more severe food insecurity than Naryn and Jalalabad persists across all three survey rounds.

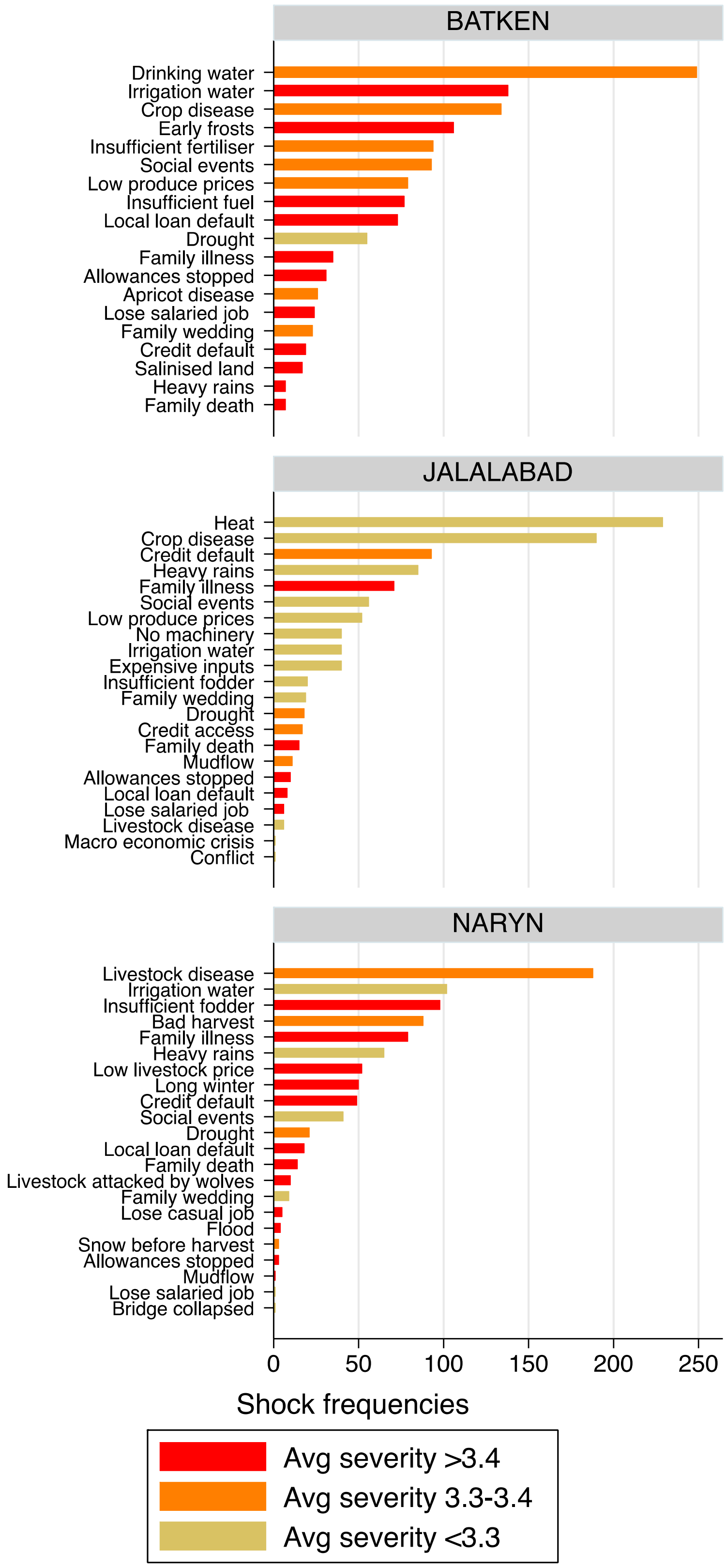
This finding is supported at the district level by other reports on food security in Kyrgyzstan (World Food Programme 2014). Nevertheless this disparity between average food security and wealth in the surveyed communities in Naryn and Batken is surprising, particularly given the relative isolation of the Naryn village (70km from nearest town and health services) compared to the Batken village (15km from nearest town and health services).

Shock & stressor occurrence and severity
A list of location-specific shocks and stressors was compiled during the focus groups, on both climate- and non-climate-related events. Amongst the non-climate-related shocks and stressors are 'social events' and 'family weddings', because these tended to put large financial strain on the households.

In the second and third rounds of the survey, respondents were asked to choose up to two climate- and one non climate-related shock or stressor that they had experienced since the previous survey, and to rate the severity of impact that it had had on their family's wellbeing, on a five-point scale: 1 ('Eventually it brought some positive outcomes'), 2 ('We handled it with no problem'), 3 ('It was a little concerning'), 4 ('It was quite bad') or 5 ('It was very bad').

Figure 4 displays the frequency of self-reported shocks experienced over the six months of the survey for each community, colour coded in three quantiles according to the average severity that respondents reported each shock/stressor had on their family's wellbeing when they experienced it. Jalalabad's reported experienced severity is lower than that of Batken or Naryn, which could either be because the shocks that Jalalabad households experienced were objectively lower in intensity, or it may be that Jalalabad respondents perceive shocks to have a less severe impact. In contrast, the reported severity of shocks/stressors in Batken is relatively high and strongly concentrated around water availability for drinking and irrigation, closely followed by agricultural factors such as crop disease, poorly timed frosts and the availability of fertilisers. Naryn has a more varied distribution of shock/stressors frequency and severity, with neither of the two most frequent shocks being rated in the highest severity quantile.

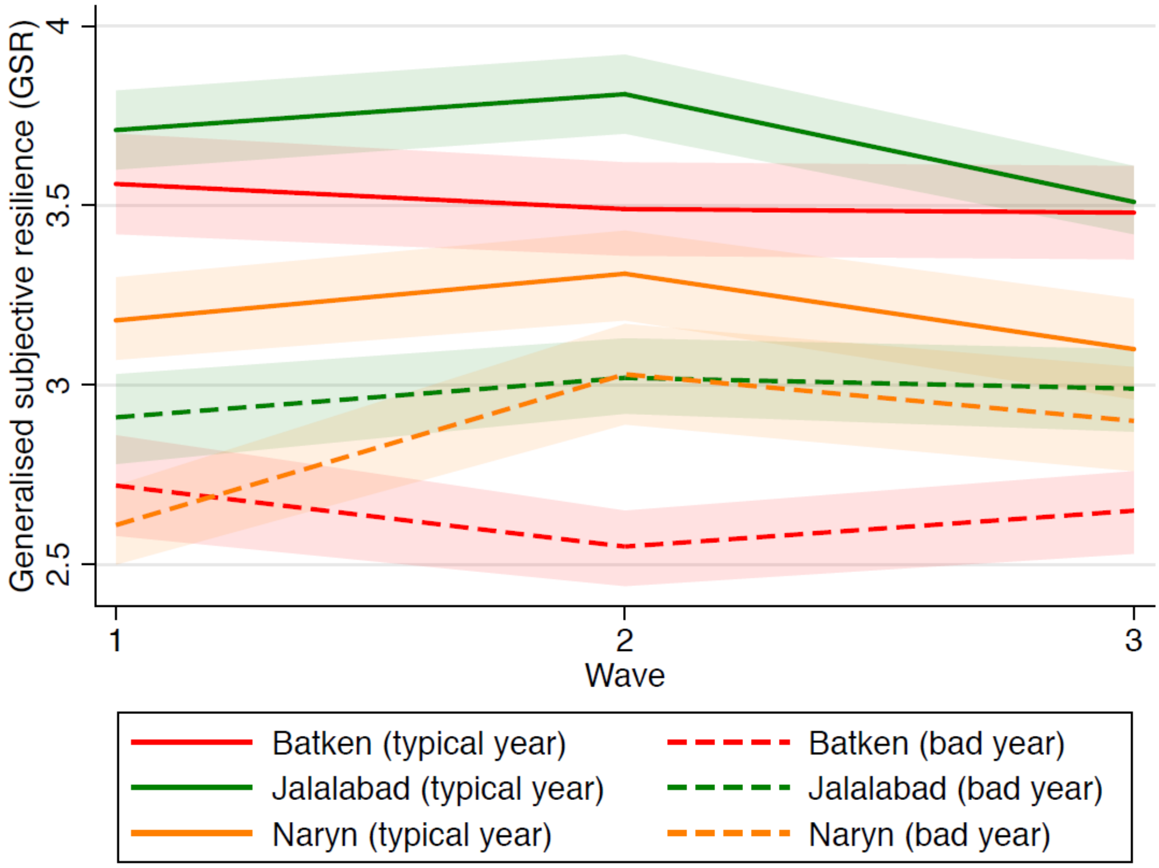
Figure 4: Frequency and severity of all shock/stressors experienced by community



Subjective resilience: Generalised and shock-specific community averages

Figure 5 displays the community-averaged generalised subjective resilience (GSR) scores for each of the survey waves in April (1), July (2) and November (3).

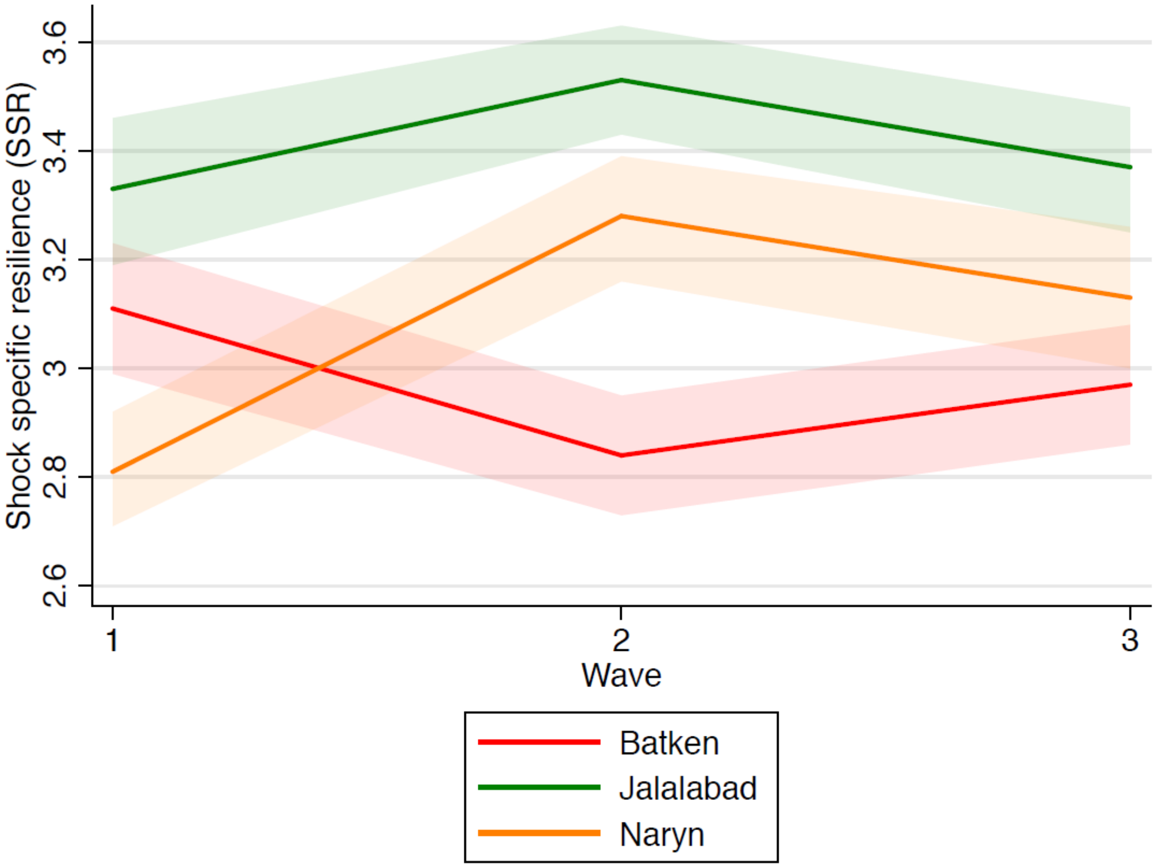
Figure 5: Average generalised subjective resilience scores in all three waves by location



Subjective resilience for a bad year was consistently lower than for a typical year both within and across locations. Comparing averages between communities, Jalalabad has the highest overall subjective resilience in typical and bad years. Batken's perceived resilience is higher than Naryn's in a typical year but lower in a bad year. Jalalabad and Naryn also appear to have higher subjective resilience in Wave 2 than in Waves 1 and 3, coinciding with the harvest season and likely abundance of food. In contrast, Batken demonstrates its lowest subjective resilience for a bad year in Wave 2, which may reflect summer and heat-related water access issues during that survey wave. Indeed, the top two shock frequencies for Batken in Figure 4 are water related and both are in the top two severity quantiles.

The community-averaged shock-specific resilience (SSR) measure follows a similar pattern (Figure 6), with Jalalabad's subjective resilience consistently higher across all three waves, and Batken and Naryn following a similar pattern to the bad year results in Figure 5.

Figure 6: Average shock-specific subjective resilience scores in all three waves by location



Analytical results
This section reports the results from regression models that test the power of generalised subjective resilience questions to predict future food security. We are only able to test the predictive power of the generalised subjective resilience questions because restricting the sample to those who rated their subjective resilience to a specific shock in Wave 1 or Wave 2 and then also experienced that specific shock between Wave 1 and Wave 3 leaves too few observations to run the models.

We use two types of regression model (in-sample and out-of-sample) to test and compare the power of subjective and objective resilience indicators in a previous time period (either W1 or W2) to predict food security in the next time period (either W2 or W3, respectively). The objective resilience indicators were chosen based on those that would typically be collected under an objective resilience assessment, specifically:

- Household socio-demographics: age, gender, and education of household members; household size; and whether any member reported earning income from external migration
- Assets: total value of household assets

In addition, data was collected on:
- Coping responses: a series of dummy variables indicating which coping responses households used in response to prior shocks and stressors
- Help received: a series of dummy variables indicating which sources of help households reported receiving in response to prior shocks and stressors

For all regression models, the subjective resilience and objective resilience indicators are taken from the survey preceding the HFIAS score used as the dependent variable. In this way we are able to test and compare the predictive power of the subjective and objective indicators.
We also control for the preceding HFIAS score (known as a 'lagged dependent variable'), and therefore can interpret these results as both predicting the *absolute level* of food security and also the *change in level* of food security between surveys simultaneously, as they are mathematically equivalent.

In-sample models: Subjective resilience is a strong independent predictor of food security
Table 4 displays the correlation coefficients for four regression models, each using the HFIAS index as the outcome variable, controlling for community fixed effects and including the lagged dependent variable. This table displays only those coefficients that were significant in at least one model. Model 1 includes only objective measures of resilience and demonstrates that level of household assets is a strong positive predictor of HFIAS. In addition, households that report reducing food quality/quantity, taking a loan, receiving family help or sending a family member to migrate as a result of shock/stressor experiences also tend to have higher food security. Interestingly, receiving government help is a significant negative predictor of food security. These associations and their significance remain largely unchanged across Models 2, 3 and 4, which add in the generalised subjective resilience indicators for a typical year only (model 3), a bad year only (model 3) and then both a typical and bad year together (model 4), respectively. When used alone, the typical and bad year indicators are both strong positive predictors of future food security, but when included together only the typical year indicator is a strong predictor, suggesting that they are tapping into a similar mental construct. Moreover, the robustness of the other indicator coefficients to the addition of subjective resilience indicators suggests that the subjective questions are explaining variation in future food security that has not been captured by the other variables.

This notion is further supported by Table 5, which regresses future food security on generalised subjective resilience in a typical year and successively adds sub-groups of other variables to investigate how they impact the subjective resilience coefficient size and significance. Adding the lagged dependent variable has the most significant impact on the subjective resilience coefficient size; however the significance of the subjective resilience coefficient stays high across all model permutations, again suggesting that the metric is capturing variation in future food security that the objective resilience measures are not. Appendix C presents the same analysis using the bad year subjective resilience indicator, showing broadly the same pattern of significance.

Table 4 – Associations between generalised subjective resilience and HFIAS score

models	(1)	(2)	(3)	(4)
SUBJECTIVE MEASURES				
Normal shock impact		0.59^{***}		0.59^{***}
		(0.15)		(0.16)
Bad shock impact			0.27^{**}	0.02
			(0.13)	(0.14)
SOCIO-DEMOGRAPHICS				
Assets (log)	0.43^{***}	0.43^{***}	0.44^{***}	0.43^{***}
	(0.11)	(0.11)	(0.11)	(0.11)
Female head	-0.11	-0.15	-0.09	-0.15
	(0.20)	(0.21)	(0.21)	(0.21)
Education	0.12	0.10	0.11	0.10
	(0.13)	(0.13)	(0.13)	(0.13)
Number HH member	-0.02	0.00	-0.01	0.01
	(0.08)	(0.08)	(0.08)	(0.08)
Age	-0.02	-0.02	-0.01	-0.02
	(0.04)	(0.04)	(0.04)	(0.04)

Age squared	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
External migration dummy	0.58*	0.62**	0.56*	0.62**
	(0.30)	(0.29)	(0.30)	(0.30)
COPING STRATEGIES				
Asset sale	0.03	0.18	0.10	0.19
	(0.24)	(0.25)	(0.25)	(0.25)
Reduced food quantity or quality	0.78**	0.95***	0.79**	0.96***
	(0.32)	(0.33)	(0.32)	(0.33)
Reduced household spending	-0.00	0.09	-0.02	0.07
	(0.27)	(0.26)	(0.27)	(0.26)
Took a loan	0.58**	0.56**	0.60**	0.56**
	(0.27)	(0.27)	(0.27)	(0.27)
Migrated away from family home	-0.54	-0.64*	-0.54	-0.64*
	(0.34)	(0.33)	(0.33)	(0.33)
Worked for others	0.22	0.25	0.24	0.26
	(0.30)	(0.30)	(0.30)	(0.30)
HELP RECEIVED				
Family	0.54**	0.45*	0.54**	0.46*
	(0.26)	(0.26)	(0.26)	(0.26)
Local Community	0.04	-0.03	0.13	-0.02
	(0.36)	(0.36)	(0.36)	(0.36)
Government	-1.21***	-1.33***	-1.27***	-1.33***
	(0.41)	(0.41)	(0.41)	(0.41)
NGO	0.42	0.41	0.42	0.41
	(0.60)	(0.59)	(0.61)	(0.59)
N	1164	1163	1162	1162

Dependent variable is HFIAS. Clustered SE are in parentheses.

Table 5 – Investigating the in-sample predictive power of generalized subjective resilience measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Typical year subjective resilience	1.71*** (0.20)	1.81*** (0.19)	1.81*** (0.19)	0.45*** (0.15)	0.47*** (0.15)	0.42*** (0.15)	0.54*** (0.15)
Community Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Lagged dep variable	No	No	No	Yes	Yes	Yes	Yes
Demographics controls	No	No	No	No	Yes	Yes	Yes
Asset control	No	No	No	No	No	Yes	Yes
Coping & help received controls	No	No	No	No	No	No	Yes
N	1168	1168	1168	1168	1167	1163	1163
r2	0.11	0.17	0.17	0.42	0.42	0.43	0.45
Elasticity	0.15	0.16	0.16	0.04	0.04	0.04	0.05

Dependent variable is future HFIAS. Clustered SE on households are in parentheses.

As a further robustness check, we tested the predictive power of subjective wellbeing (measured by the Satisfaction With Life scale) alongside that of the subjective resilience questions, in order to investigate whether a subjective appraisal of one's life satisfaction is accessing a distinct mental construct to a subjective appraisal of one's resilience.

Table 6 demonstrates that subjective wellbeing has a slightly significant positive relationship to future food security when added to a model without other subjective resilience indicators included as independent variables (Model 1). However the addition of the typical year subjective resilience indicator (Model 2) leaves the Satisfaction With Life coefficient near zero and insignificant. This attenuation suggests that there is something specific to the GSR measures used here that creates forward looking predictive power for food security that is not observed in a more general subjective appraisal of life satisfaction and wellbeing.

Table 6 – Comparing the predictive power of subjective wellbeing and subjective resilience

	(1)	(2)
Satisfaction With Life Scale	0.04*	0.01
	(0.02)	(0.02)
GSR: Typical year		0.42***
		(0.15)
Community FE	Yes	Yes
Wave FE	Yes	Yes
Lagged dep variable	Yes	Yes
N	1169	1168
r2	0.42	0.42

Dependent variable is future HFIAS. Clustered SE on household are in parentheses.

Out-of-sample models: A single subjective resilience indicator has the explanatory power of many objective indicators combined

Having established that the generalised subjective resilience indicators are strong independent in-sample predictors of future food security and additionally tap into a distinct subjective assessment to life satisfaction, the next analysis tested their predictive power for out-of-sample data and compared it with the explanatory power of the objective variables. This was achieved using the leave one out cross validation (LOOCV) method, which is particularly relevant to applied resilience practitioners, as governments and NGOs may need to predict future outcomes (so-called 'out-of-sample') using only current information.

Each LOOCV run removes one observation from the sample and then uses the remaining data points to produce a model that calculates the predictive power of specified independent variables. This model is then used to predict the value of the left-out observation and its accuracy in doing so is reported as the squared error. This process is repeated for all observations and the squared errors are summed, creating the total root mean squared error (RMSE).

The RMSE is an indicator of how well a certain model (made up of a combination of objective and/or subjective indicators) can predict future household food security or coping strategies. We therefore calculate the RMSE for a range of different models with and without subjective and objective resilience indicators to assess their predictive usefulness, thus determining what value the inclusion of subjective resilience indicators may have for NGOs and policy makers that are seeking a predictive indicator of resilience.

Figure 7 displays the root mean squared errors (RMSE) for a range of LOOCV models that include various combinations of subjective and objective resilience indicators, regressed on HFIAS score. The RMSE values are on the same scale as the outcome variable, so a RMSE of 3.6 means that on average the out-of-sample prediction error is 3.6 points on the HFIAS scale. Therefore a smaller RMSE indicates a smaller prediction error and thus greater predictive power of the combination of subjective and/or objective variables that are included in each model.

Figure 7 displays the RMSEs of six models all using HFIAS score as their outcome. The combinations of objective and subjective variables included in each model is displayed in Table 7, and the x-axis in

Figure 7 displays the RMSEs of these models with the subjective resilience (SR) typical year indicator (left group), the SR bad year indicator (centre group) and no SR indicator (right group) included.

Table 7 – Combinations of objective and subjective indicators included in LOOCV models

	M00	M0a	M0	M1	M2	M3
Logged assets		X		X		X
Socio-demographic indicators			X	X	X	X
Coping responses					X	X
Help received					X	X

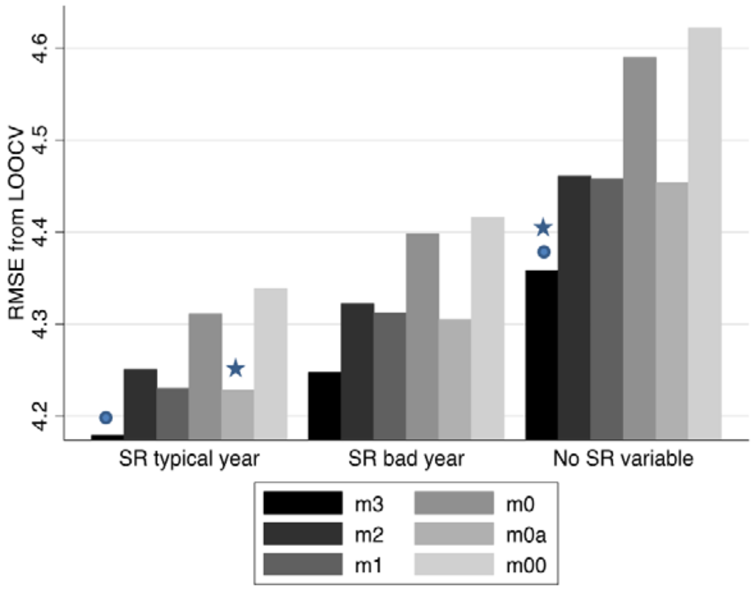
The results in Figure 7 reveal that adding either the typical year or bad year subjective resilience indicators always reduces the RMSE in comparison to the equivalent model with no subjective resilience indicator. For example, comparing the size of the bars identified by the circles (which represent the RMSE when all objective indicators are used without a subjective indicator (right circle) and then with a subjective indicator (left circle)) it is clear that the addition of just one subjective resilience indicator to the many other objective indicators decreases the prediction error substantially.

However, even more striking is the comparative prediction error sizes for M3 without any subjective resilience indicators (right side star) versus M0a including the 'typical year' subjective resilience question (left side star). In this case the prediction error from asking simply the typical year generalised subjective resilience questions and assets is lower than when asking about socio-demographics, assets, coping strategies and help received in response to past shocks and stressors. In essence, the variation captured in that one subjective resilience question covers the variation captured by over ten others. The same relationships hold constant when varying the inclusion of the lagged dependent variable and community fixed effects (see Appendix D.)

Overall these model comparisons suggest that subjective resilience indicators are good out-of-sample predictors of food security, particularly when used in tandem with objective resilience indicators such as assets. Moreover it appears that the predictive power of a single subjective resilience question is stronger than that of many objective indicators combined, which could have significant results for the length of the surveys that are used to create resilience indices that aim to quantify resilience level.

Nonetheless, the model with the best predictive power is that which includes all of the objective indicators plus the GSR typical year question.

Figure 7 – RMSEs without lagged dep variable (HFIAS) and with community fixed effects are smaller when including the GSR indicator to a model with only assets (stars) or with all other objective indicators (circles)

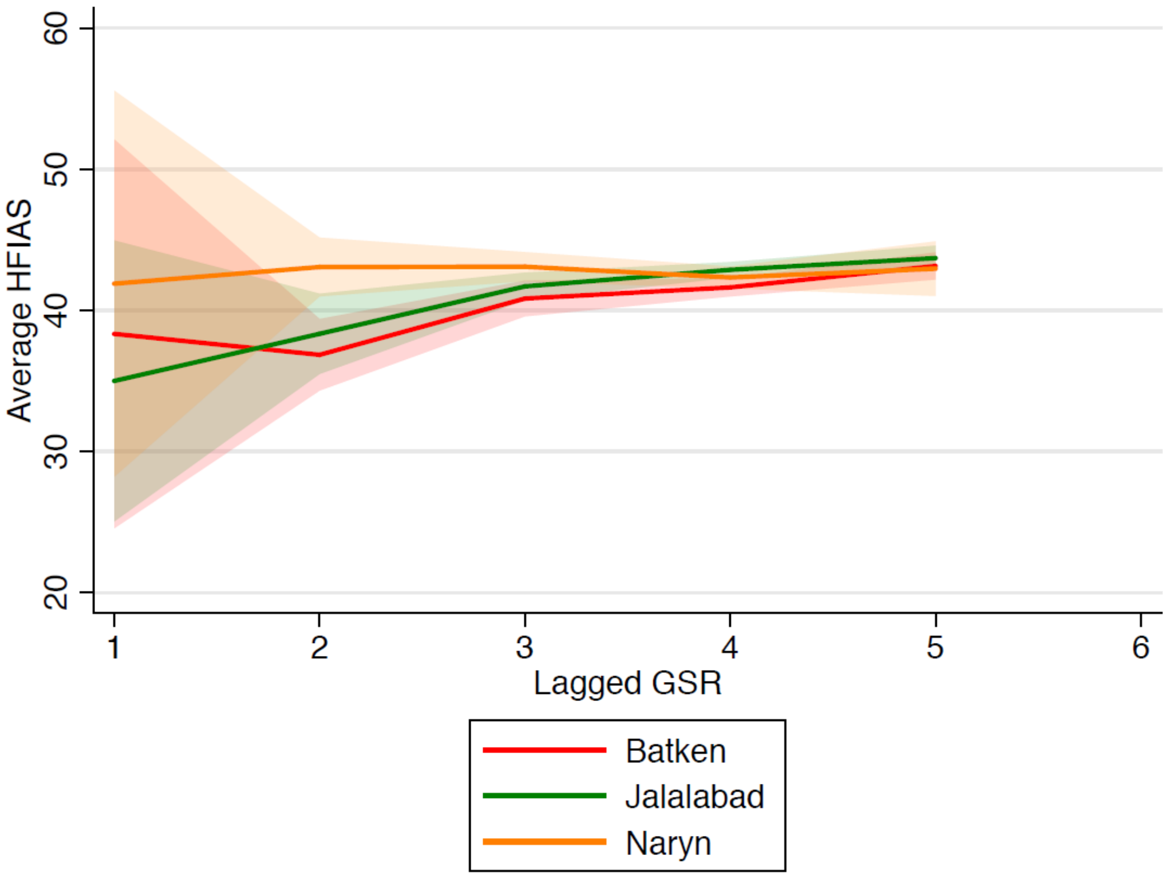


Are subjective resilience indicators comparable across contexts?
So far these results provide promising evidence that subjective resilience indicators could be reliable predictors of future food security and have strong predictive power compared to alternative objective indicators. The third and final step of our analysis was then to test the cross-context comparability of the subjective resilience indicators, for example, to test whether a GSR score of 3 for households in completely different contexts would lead to a similar future food security score. If this were true, it would enable us to predict the likelihood of a household remaining food secure in the face of shocks and stressors that are idiosyncratic to them and their specific context, thus allowing the comparison of resilience levels across space, which could be extremely useful for targeting programme funding to the least resilient households and/or communities.

To assess this cross-context comparability, we run regression models using food security as the dependent variable and typical year GSR from the previous time period ('lagged') as the independent variable for each of the three case study locations, controlling for whether the household experienced a high shock severity (using a dummy variable) in the time period between measuring the typical year GSR indicator and the food security indicator. We then compare the values of future food security that the lagged GSR indicators predict in each location and check whether their confidence intervals overlap (see Figure 8).

The confidence intervals at GSR scores below 2 are very wide due to a lack of data points. At a GSR score of 2, the distributions for Batken and Naryn are not overlapping, but at a GSR score of 3 and above all three distributions overlap, suggesting that some cross-context comparability may be possible when using subjective resilience measures. However, arguably it is at the lower levels of resilience that it is most important to have accurate predictions of future food security across contexts, and therefore more work is needed to test these measures more robustly across space with larger data sets.

Figure 8 –Relationship between GSR and average HFIAS score across locations



DISCUSSION

The search for a resilience measurement tool that can predict future wellbeing in the face of shocks and stressors is at a relatively early phase of development. Similar attempts to develop standardised quantitative indicators for latent social constructs such as psychological resilience, food security and wellbeing have been ongoing for a decade or more, and it is interesting to note that in each case the initial focus was on objective indicators, and that over time the emphasis shifted to either include subjective indicators alongside objective ones (e.g., the HFIAS for food security (Coates et al. 2007), or the OECD Better Life initiative for wellbeing (Boarini et al. 2014)) or to create solely subjective scales (e.g., the Resilience Scale for Adults (Friborg et al. 2003), or the Satisfaction With Life Scale for wellbeing (Diener et al. 1985)).

Similarly the early stage application of resilience theory to the CA and DRR contexts has been marked by a proliferation of objective resilience measurement tools. These tend to deconstruct resilience into many sub-capacities, assign one or more indicator to measure each sub-capacity, and then combine the values for each of those indicators into a number that meaningfully captures the resilience level of the respondent (Ciani 2013; D'Errico, Garbero, et al. 2016; FAO 2016). However, noting that each step of that complex process is fraught with uncertainty regarding the whats, whys and hows of measurement, subjective approaches to measurement are increasingly acknowledged as a complementary methodology (Smith & Frankenberger 2015; Béné et al. 2016; Maxwell et al. 2015; Jones & Tanner 2016) and have been suggested to offer three potential areas of added value to resilience measurement: (i) as valid and reliable predictors of future wellbeing levels, (ii) as a way to reduce the questionnaire burden on respondents, and (iii) as a tool that ay provide cross-contextual comparisons of resilience (Clare et al. 2017). This research is a first attempt to empirically explore these possibilities. The following discussion will review the extent to which the evidence presented here can support these claims, and highlights where more work is needed to continue the research and clarify our understanding of how subjective approaches can add value to resilience measurement in the context of CA and DRR.

Can subjective resilience measures predict future wellbeing?

In common with much of the existing literature (FAO 2016; Jones et al. 2018; Béné et al. 2016) the in-sample regression analyses presented here emphasise the important role of assets, family networks and access to financial services in maintaining wellbeing in response to challenging events (Nelson et al. 2007; Jordan 2015; Newman & Dale 2005). However, the current findings suggest that subjective resilience indicators may also be strong predictors of future food security, and seemingly capture variation in food security levels that is not explained by the many other variables in the model (socio-demographics, assets, coping strategies and help received). This relationship makes sense when considering that resilience is likely to be influenced by many intangible factors that are extremely difficult to measure objectively (Levine 2014; Brown 2014) but that are likely to be factored in carefully to a subjective assessment of overall resilience levels.

Moreover, the GSR indicator remains a strong predictor even when measures of lagged wellbeing are taken into account. In Table 5, the addition of the lagged HFIAS (i.e., the HFIAS score in the time period prior to the one being predicted) reduces the size of the GSR coefficient but the latter still remains highly significant. In addition Table 6 demonstrates that the explanatory power of subjective wellbeing is not as strong as that of GSR at predicting future food security. Overall this finding suggests that the GSR indicator is not simply an appraisal of current wellbeing that happens to predict future wellbeing, but that there is additional predictive power in asking people about their level of confidence to maintain their wellbeing in the face of shocks and stressors.

Can subjective measures reduce the questionnaire burden on respondents?
This study offers some of the first evidence that subjective resilience questions could be used to reduce the length of resilience surveys, where ascertaining the level of resilience for a household is the main aim. Evidence from the out-of-sample analyses suggests that using data on total household asset value combined with just the typical year GSR indicator has a lower predictive error for future food security than a model consisting of many objective indicators of household socio-demographics, assets, coping responses and help received (Figure 7). Theoretically this could mean that using simply a questionnaire including metrics for assets and typical year GSR could be as or even more effective at future food security prediction than a much longer survey that deconstructs and then reconstructs the various sub-capacities of resilience, potentially saving significant time for respondents and survey costs for resilience-development programmes.

It is important to note that this is the case only where a standardised assessment of resilience level is desired, rather than a deep, context-specific understanding of the drivers of and barriers to resilience in a particular location. Simply collecting information on asset values and GSR does not offer nuanced insight into the specific drivers of and barriers to resilience, in which case a combination of larger objective surveys plus qualitative and participatory methods would be more appropriate (Maxwell et al. 2015). However, if the sole aim of a survey is to investigate resilience levels only, then the empirical results in this paper suggest that subjective resilience measures may provide more powerful predictors of future food security than some of the standard objective indicators that are typically used.

Can subjective approaches provide cross-contextual comparisons?
Similar to other nascent social constructs, such as food security (e.g. Coates 2009; Maxwell et al. 2013), the 'holy grail' of resilience measurement would be an index that is valid, reliable and comparable over time and space (Béné 2013). Although the results presented in this paper are far from meeting such a goal, it is interesting to note some commonality in the location-specific relationships between the GSR and HFIAS at higher GSR scores (see Figure 8). The notable drawback, however, is that the context-specific variation at lower levels of GSR (where most policy and programming attention is likely to be focused) is very high and the distributions do not overlap. However this is at least tentatively positive evidence that subjective approaches could contribute to the development of a cross-contextually comparable measure of resilience in the future.

Moreover experience from the application of subjective approaches to other research fields (Diener et al. 1985; Oishi et al. 1999; Ungar & Liebenberg 2011; Liebenberg & Moore 2016; Kahneman & Krueger 2006) suggests that they may hold promise when comparing complex constructs across very different situations. To take subjective wellbeing as an example, the cross-contextual comparability is created because the questions leave the definition of what a 'good standard of life' is within the mind of the respondent, and simply ask them the extent to which they have attained that self-defined standard, rather than asking them to specify what exactly that good life looks like (Clare et al. 2017; Pavot & Diener 1993; Oishi et al. 1999). Relatedly, subjective approaches to resilience measurement would avoid trying to compare the specific objective characteristics of a situation, and rather aim to measure confidence of respondents that they can maintain their wellbeing in light of their given situation. In effect, subjective measures try to measure the 'resilience gap' between how the respondent perceives their current situation to be, and how they feel it needs to be (Clare et al. 2017), and it is this gap that may feasibly be compared across contexts.

Next steps for subjective resilience research
This study has provided some of the first empirical evidence that subjective resilience measures may be as good predictors of future food security as more objective indicators, and has opened the

conversation on their use as a cross-contextually comparable indicator. These findings provide a sound basis from which to encourage more detailed research into the design and structure of such questions. For example, investigating whether shock-specific versus generalised questions are more accurate and/or informative for policy and programming purposes, or exploring whether a multi-item index similar to those used in psychological resilience and subjective wellbeing research could reduce the prediction error even further.

Notably, the subjective indices from other research fields that have had some success in translating across contexts are made up of multiple complementary questions that have been developed as a unified scale and are designed to be analysed as a whole rather than individually. In contrast the subjective measures in this study were single questions, and are therefore likely to introduce more noise into the data due to their vulnerability to small variations in wording (Veenhoven 2011). As such future investigations of cross-contextually valid subjective resilience measures could benefit from developing and testing a number of a multi-item scales.

Given the promising results reported here it may also be appropriate to investigate the potential of subjective measures for monitoring purposes. Our results indicate that community-averaged subjective resilience scores varied over time, and seemingly in response to events that occurred (e.g., Batken's subjective resilience scores dipped lower than those in Naryn and Jalalabad, and respondents in Batken also reported the highest severity of shocks during the survey period.) Therefore it seems that despite the GSR measures being phrased in annual terms (i.e., how confident the respondent is that they can maintain their family's wellbeing in a good or bad *year),* people's responses were being affected by shorter-term influences. If this is the case, it could be a desirable trait for a resilience measurement tool, which should ideally be responsive to short-term changes in socio-environmental conditions that have the potential for negative impacts on household wellbeing (Barrett & Headey 2014; Béné et al. 2015).

CONCLUSIONS

This paper presents the first empirically tested evidence that subjective resilience measures can be significant predictors of future food security in the face of shocks and stressors. The results are an encouraging addition to a relatively new field of research that may have much to offer CA and DRR resilience practitioners through accurate identification of more or less resilient households using shorter more efficient surveys than those currently in existence. There is also some theoretical justification and applied evidence from the fields of subjective wellbeing and psychological resilience that subjective approaches can be useful in developing cross-contextually comparable indicators. However much more work is required on the structure and design of these measures before this can be applied in the CA and DRR arenas.

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