MEASURING CLIMATE RESILIENCE AND VULNERABILITY:

A CASE STUDY FROM ETHIOPIA

FINAL REPORT

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ABBREVIATIONS

3W map	Who is doing What and Where map
AIC	Aikake Information Criteria
ATCP	Air Time Credit Purchases
CDR	Call Detail Records
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CI	Confidence Interval
DfID	Department for International Development
DLNM	Distributed Lag Non-Linear Model
DRM	Disaster Risk Management
ENBCCA	Ethiopian Nile Basin Climate Change Adaptation Dataset
ERHS	Ethiopia Rural Household Survey
FAO	Food and Agriculture Organisation
FEWS NET	Famine Early Warning Systems Network
FGT	Foster-Greer-Thorbecke
FSIN	Food Security Information Network
GPCC	Global Precipitation Climatology Centre
HICE	Household Income and Consumption Expenditure
IGAD	Intergovernmental Authority on Development
IPCC	Intergovernmental Panel on Climate Change
LCOT	Livelihood Change Over Time
LEAP	Livelihoods, Early Assessment and Protection
LSMS	Living Standards Measurement Study
NDVI	Normalized Deviation Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
OCHA	Office for the Coordination of Humanitarian Affairs
OLS	Ordinary Least Squares
PET	Potential Evapotranspiration
PRIME	Pastoralist Areas Resilience Improvement and Market Expansion
PSNP	Productive Safety Net Program
RCT	Randomized Controlled Trial
RIMA	Resilience Index Measurement and Analysis
SNNP	Southern Nations, Nationalities and Peoples' Region
SPEI	Standard Precipitation Evapotranspiration Index
SPI	Standard Precipitation Index
UN	United Nations
USAID	United States Agency for International Development
USD	United States Dollar
WB	World Bank
WRSI	Water Resource Satisfaction Index

EXECUTIVE SUMMARY

INTRODUCTION

In the face of recurrent crises across many countries that negatively affect national economies, undermine the impact of investments, and all too often lead to extremes of human suffering, USAID has taken the lead in forming a global partnership to promote the resilience of vulnerable populations through investments that enhance their capacity to mitigate, recover and adapt to shocks and chronic stresses. A key promise of the resilience concept is to bridge the gap between humanitarian and development actions and to provide "an overarching organizational scheme within which vulnerability, shocks, and heterogeneity of recovery pathways may be measured" [1].

However, despite its emergence as a central narrative in international development, resilience research has yet to catch up to policy and practice. This new emphasis on resilience in humanitarian and development programming requires a set of practical, widely-available and efficient measurement tools that can effectively distinguish between poverty, vulnerability and resilience, and provide the basis for an evidence-based resilience strategy that addresses each of these critical dimensions of human welfare. Development of an effective measure of both vulnerability and resilience is, therefore, critical in order to support more effective and sustainable investments that reduce the cycle of emergencies among vulnerable populations, improve their lives, increase stability and security, and decrease the need for repeated humanitarian interventions.

This report introduces a new comprehensive framework to simultaneously estimate individuals' vulnerability and resilience to climate shocks such as droughts and floods. Ethiopia was selected as a case study for four main reasons: (1) it is vulnerable to climate shocks across much of the country [3-5]; (2) it is one of the larger net recipients of development assistance in Africa [6]; (3) it presents a large diversity of the agro-ecological zones typically found in Sub-Saharan Africa; and (4) it provides an abundance of rich datasets that are particularly well-suited to this analytical task.

Indeed, a stumbling block for resilience measurement is the dearth of high frequency household panel data in most developing countries that would provide insights into the relationship between climate shocks and relevant household-level variables. The Ethiopian panel datasets and the modeling strategy used in this study allow for the assessment of those relationships over a prolonged period of time. However, they also allow for the testing of a novel statistical modeling technique that allows for the estimation of a resilience measure from a single cross-sectional survey, using only a time series of climate observations. If successful, this method will allow for rigorous resilience measurement across a wide number of countries for use in policy and program design, targeting, impact evaluation and early warning.

DEFINITION

The utility of *resilience* in designing and evaluating interventions depends largely upon how it is defined. The international development sector has proposed myriads of definitions for the concept. Emerging from the many definitions are at least two distinctive characteristics of resilience: (1) the capacity to withstand a shock and (2) the capacity to bounce back after a shock. The first can be understood as the absence of vulnerability, which essentially involves a normative goal of preventing individuals from falling into a poverty trap. The second is more dynamic; it is the ability of individuals to recover to the original or an improved level of well-being.

With an eye towards specific policy inference and impact attribution, we choose to adopt a *narrow* view of resilience. The narrow view sees resilience as distinct from the already well articulated concepts of poverty (a snapshot of well-being at a particular point in time) and vulnerability (an ex-ante assessment of expected poverty). Within the narrow lens, the added value of resilience is its focus on dynamics: the poverty pathway over time. We therefore define and measure resilience as the speed of recovery after a shock.

Narrow definition of resilience

1. Poverty: Observed at a specific time period. A household is poor if its level of consumption is below a given reference point, such as an official poverty line.
    - For the poor household in Plot A, poverty in time period 1 is represented by distance ***A***.
    - The non-poor household in Plot B is above the poverty line in time period 1.
2. Vulnerability: An ex-ante, or forward-looking prediction of future poverty. Both households are expected to experience a shock in period 2; their vulnerability is represented by distance ***B***.
    - For the poor household, vulnerability is the difference between the initial level of consumption and post-shock consumption.
    - For the non-poor household, it is the difference between the poverty line and post-shock consumption.
3. Resilience: A dynamic assessment of how a household will react in the event of a shock. If a household takes a long time to recover, the household lacks resilience. Households who bounce back more quickly are resilient. This is represented by the line ***C***.
    - For both households, resilience is measured from the time period with lowest consumption to the time period in which the household has recovered to its pre-shock consumption level.

In order to measure vulnerability and resilience, we define the following set of indices:

- The **weather vulnerability index** is a measure of the expected poverty gap caused by an adverse weather shock and is designed to summarize weather sensitivity. For individuals above the poverty line, this is the difference between consumption during hazard-induced conditions and the poverty line. For individuals below the poverty line, it is the difference between consumption in hazard-induced conditions and consumption in normal conditions. It can be fitted to droughts and floods of various magnitudes.

- The **climate vulnerability index** is the average weather-induced poverty gap, given the expected distribution of all weather shocks of different magnitudes over time. It is expressed as a percent of the poverty line. This measure answers the following question: what is the expected increase in the poverty gap next year if a weather shock (drought or flood) occurs? This measure is distinct from the weather vulnerability index in that it does not refer to a specific shock of a given magnitude, but, again, reflects the expected or average weather-induced poverty gap, given the probability of all shocks.

- The **weather resilience index** is the expected speed of recovery after a given weather shock. Again, it can be fitted to droughts and floods of various magnitudes. This measure answers the following question: when will the household be back at the pre-shock level? It is defined in reference to a five-year time frame, which is the average frequency of a significant weather shock. A household able to recover within five years is considered resilient. However, a household needing more time is at risk of being affected by a second drought when still recovering, which could trigger a downward spiraling trajectory. It would, therefore, be considered not resilient. Given this five-year frame of reference, households taking less than five years to recover receive a positive score and those who recover in more than five years receive a negative score.

- Finally, **the climate resilience index** is the average recovery time, given the expected distribution of weather shocks of different magnitudes. Again, this measure is defined in reference to a five-year time frame. It answers the following: what would the expected recovery time be if a weather shock were to happen? Would the household be able to recover in less than five years? The climate resilience index is distinguished from the weather resilience index by the fact that we do not specify the type of shock (e.g. a major drought). Rather, we just want to know in general how quickly the household recover on average given any deviation from normal weather conditions.

Within this framework, welfare can be addressed along three dimensions: eradicating poverty, alleviating vulnerability and building resilience. Each dimension is measurable in its own right, and is associated with a specific set of policies (see Box below), enabling policy makers to identify the right policy mix for a particular population group. Because they are based on standard poverty measures and recovery time, these indices are directly comparable across interventions and countries.

Classification of policies

Chronic poverty reduction policies for long-term equitable growth:

- Economic growth (e.g. through macro policies and investment)
- Redistribution (e.g. through regular cash transfers, land reform)
- Market policies
- Improved public services (e.g. education and healthcare)

Vulnerability reduction policies to avoid the full brunt of the shock:

- Risk reduction (e.g. drainage, irrigation, livelihood diversification)
- Early warning systems
- Emergency stocks

Resilience building policies for hastened recovery:

- Public and private insurance
- Post-crisis recovery investments
- Adaptive capacity / ex-post risk coping capacities (e.g. direct delivery of cash, food or non-food and DRM)
- Graduation systems to ensure recovery when the ex-post intervention ends

METHODS

The foundation of our model is the relationship between any risk process and the human outcome of interest over time. We apply the model to the specific relationship between the severity of a weather shock and the change in consumption over time, although the method could equally be applied to other types of risk, and other health or economic outcomes. Once the relationship between climate and consumption is clearly established by the model, we then summarize the results in our vulnerability and resilience indices. Essentially, the vulnerability indices summarize the climate-consumption relationship, while the resilience indices summarize the time-consumption relationship.

Although many measures were tested in the development of the model, we rely on the Standardized Precipitation Evapotranspiration Index (SPEI)[1] [7] as the key weather risk variable. We use food consumption, obtained from three extensive household income and expenditure datasets from Ethiopia: the Ethiopia Rural Household Survey (ERHS), that provides a multi-round panel data series from 1994 to 2009; the Ethiopian Nile Basin Climate Change Adaptation Dataset (ENBCCA), a dual-round panel series from 2005 and 2012; and the Ethiopia Living Standards Measurement Study (LSMS), which is a nationally representative, cross-sectional household survey from 2012.

The use of secondary data ensures that the methodology is easily replicable at low cost and can be employed in situations in which primary data collection is not practical or possible. The time series SPEI data also allows for an assessment of actual weather patterns over a prolonged period of time, fully capturing the incidence of multiple weather shocks in each location on an objective scale that is comparable across locations.

Finally, we use two different estimation techniques in our analysis. The first involves using standard ordinary least squares (OLS) regressions to estimate the climate-consumption relationships in the single-period context. Using this method, it is possible to calculate vulnerability indices, but not resilience indices. The second technique employs a novel distributed lag non-linear model (DLNM) [8, 9]. The DLNM can account for consumption dynamics, allowing us to estimate the multi-period model, calculating the climate and time dimensions simultaneously from cross-sectional datasets. While the DLNM can calculate both vulnerability and resilience scores, because it is such a novel technique, we estimate it alongside the OLS model in order to compare the resulting vulnerability scores.

Using traditional estimation techniques, resilience measurement approaches generally require microeconomic panel data, preferably of high frequency, to directly analyze consumption dynamics. However, panel datasets are costly to collect and, where they are available, they are collected at low frequency. The properties of the DLNM model are such that it does not *require* a panel dataset to estimate resilience. Relying strictly on the variation in the time series weather shock variable around one period of data on consumption, the DLNM can capture the relationship between consumption and time from a single cross-sectional dataset. To demonstrate how the DLNM model allows for resilience analysis with cross-sectional data, we calculate both vulnerability and resilience indices using the cross-sectional LSMS dataset.

An additional benefit of the DLNM's reliance on climate data for dynamics is that it allows us to measure the cumulative effect of shocks, such that we can estimate the impact of repeated (or "double-bang") shocks. Although a household might be able to cope with an isolated drought, two abnormally dry years might exceed its absorptive capacity and send it on a downward trajectory. The DLNM model is perfectly suited to provide estimates of vulnerability and resilience with respect to such double-bang droughts.

Given the DLNM's many positive attributes, the newness of the approach does suggest some limitations, which are described in some detail. For example, the model cannot yet be applied to panel datasets, limiting its use in the context of impact evaluations. However, the pace of research on the DLNM

[1] SPEI is a measure of precipitation minus evapotranspiration. In other words, it is the value of the net balance of water in the ecosystem.

suggests it will be an increasingly flexible and useful approach for vulnerability and resilience measurement in the future.

RESULTS

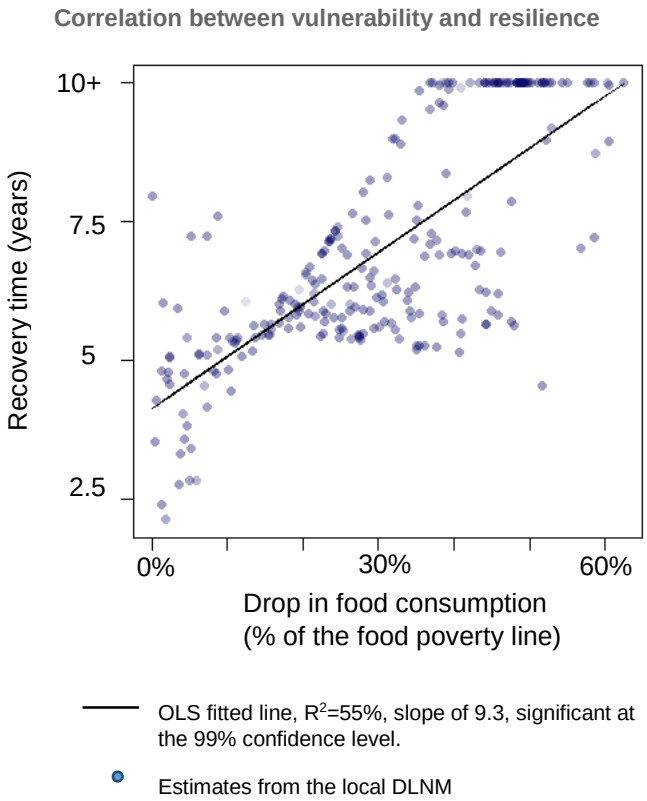
The analysis was undertaken in a series of steps. Using the LSMS dataset, we first tested a number of specifications of the climate risk variable, as mentioned above. For each variable, we estimated two specifications: one with only the weather variable and one with an added set of control variables. The best results, both in terms of the explanatory power (R-squared) and the precision of the estimates (p-values), were obtained with the Standardized Precipitation Index (SPI) and two versions of the Standardized Precipitation Evapotranspiration Index (SPEI), a base measure as defined by Beguería and Vicente-Serrano [7] (SPEI base) and a newly-created version of the indicator based on data developed by NOAA (SPEI NOAA).

We then compared the stability of the model across all household datasets by looking for consistency in the coefficients of the weather variables between the model with controls and the model without controls. The majority of the dataset combinations produce stable results, although the SPEI-base indicator performed slightly better than the others. Although the SPEI-NOAA indicator has a better spatial resolution than the SPEI-base, its results were not stable for the LSMS dataset. Although the remainder of the analysis uses the SPEI-base indicator, the potential benefits of using the SPEI-NOAA indicator warrant additional research in order to improve its performance within this framework.

Using a standard OLS regression model, we then estimated the weather and climate vulnerability indices for poor households in each of the datasets to examine how the results vary across data sources. The climate vulnerability indices suggested that on average, weather shocks were expected to lower consumption by 10% among the sample of the ERHS dataset, by 16% for the LSMS sample, and by 22% for the ENBCCA sample. Similarly, for the weather vulnerability index, we tested for a drought severity at a level expected to occur only once every 10 years. By that measure, the decline in consumption level was estimated to be 17% for the ERHS sample, 27% for the LSMS sample, and 37% for the ENBCCA sample. The variation in these weather and climate vulnerability measures across surveys warrants additional examination, but is likely due to differences in the spatial and temporal coverage of the surveys.

Beyond serving as a general rallying cry to improve coordination between development and humanitarian players, an essential question is: Does the resilience concept add substantively to our policy analysis toolkit? Does “resilience” add evaluative insight that is not already captured in the ample literature on poverty and vulnerability? In order to shed light on this question, to determine if vulnerability and resilience are empirically distinct, we tested whether weather vulnerability and weather resilience vary together, whether households with similar degrees of weather vulnerability exhibit different levels of resilience and, vice-versa, whether households with similar levels of resilience have differing degrees of vulnerability.

According to the figure below, recovery time depends strongly on the magnitude of the initial drop in consumption after a shock. For every 10 percent decline in consumption, the average recovery time increases by approximately 0.93 years, as shown by the OLS fitted line. Overall, 55 percent of the variation in recovery time is explained by the initial drop in consumption. While resilience is clearly not independent from vulnerability, neither is it the inverse of vulnerability. These findings suggest that it is, therefore, legitimate to consider the resilience concept separately from vulnerability and that the concept does add value to the assessment of household well-being. Additional work is still necessary to test whether resilience is similarly distinct from poverty.

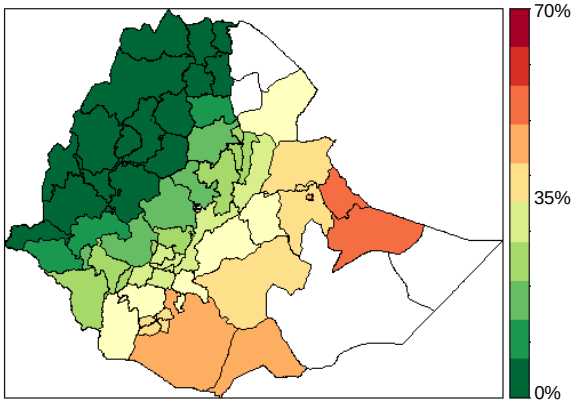


The map below provides a spatial representation of estimates of (A) weather vulnerability (in terms of the drop in consumption resulting from a 10-year return drought) and the corresponding estimates of (B) weather resilience (in terms of the estimated recovery time from a similar 10-year return drought), derived from the LSMS dataset and using the DLNM estimation technique. For (A), zones in red are expected to face a sharp drop in consumption from a given drought, while the consumption of households in green zones will be only marginally affected. Zones in white represent those for which the LSMS does not provide sufficient data. For (B) on average, zones in green are resilient while zones in orange and red are not.

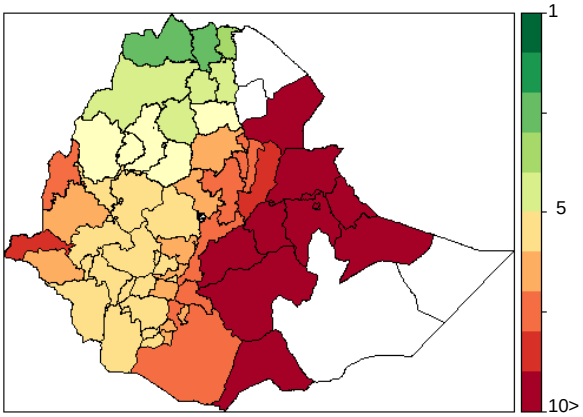
According to these maps, most parts of the country will take more than five years to recover from a drought of this magnitude. Looking at the various regions, we see that the lowlands are both highly vulnerable and not resilient with respect to a 10 years' return drought. As we would expect, some zones are both more vulnerable and more resilient than others and vice versa.

Vulnerability and resilience maps, LSMS with the DLNM model

A. Drop in consumption resulting from a 10 years return shock (% of the poverty lines)



B. Number of years to recover from a 10 years return drought



While the datasets employed in this analysis cannot strictly be used in an evaluation context to assess the impact of program exposure or participation on specific outcome variables, the ENBCCA dataset did provide an opportunity to estimate the effects of behavioral change on climate-induced consumption dynamics over time. Given the current status of the model, which requires at least three rounds of data to evaluate the impact of adaptation on resilience scores, use of the dual-round ENBCCA dataset allowed us to estimate only the overall consumption trajectory between years, rather than any change in our resilience indicators.

We conducted our analysis to test if household level climate change adaptation strategies led to a reduced effect of drought. The climate change adaptation variable is defined by whether households had made any adjustments as a result of changes in temperature, rainfall or climate. We found that climate change adaptation reduces the negative effect of drought on expected consumption.

Finally, in order to illustrate the use of the DLNM in an early warning context, we developed a food insecurity forecast for early 2016 based on the 2012 LSMS dataset. Once the dynamic relationship between weather and consumption is estimated with weather data from between 1996 and 2011, we produced forecasts of changes in consumption levels for the period 2012 to 2016. According to the model, Afar, Amhara and Tigray are all predicted to be severly affected by the current drought in 2016. In fact, the model predicts that this drought will have the most drastic consequences of any weather shock in the past 15 years, decreasing food consumption by up to 20 cents per capita day in the Afar region and 10 cents per capita day in the Amhara and Tigray regions. Conversely, while the shock will be felt in Somali, SNNP and Oromia, the resulting fall in consumption is not likely to be as severe.

The results of the forecasts compare well with the October to December 2015 FEWS NET forecast, which categorizes large parts of Afar, Amhara and Tigray as stressed or in crisis. Results also correlate well with an East Africa flood update from OCHA, which signaled displacement in the Somali region caused by flooding in 2013.

CONCLUSION AND NEXT STEPS

Research on resilience estimation and definition is still in an early stage. Our aim with this report is to contribute a new and different perspective to the field. We suggest that a *narrow* view of resilience could help to distinguish the concept from the already existing and policy-relevant concepts of chronic poverty and vulnerability. We distinguish resilience from vulnerability, as, while vulnerability analysis is concerned with the drop in well-being following a shock, the narrow view of resilience is concerned with the speed of

recovery after a shock. We provide a set of indices and techniques for measuring vulnerability and resilience to weather shocks and climate in general.

A next step is to integrate market risk into the framework, as price spikes are a major threat to household well-being in Sub-Saharan countries. Food crop price time series data are available for many markets across Africa and could be easily linked with weather and consumption data in order to gain a better understanding of the relationship between consumption dynamics, prices and weather shocks. Replicating the findings of this report in other countries would also confirm the reliability of this approach. From a methodological point of view, further research is needed on the use of interaction variables in the DLNM in order to allow for impact evaluation as well as on the use of spatially varying DLNM for early warning and policy targeting.

1 INTRODUCTION

Since the 1980's, academics and practitioners have been calling for better integration of relief and development interventions. Recently, the term "resilience" has come to serve as a rallying cry to bridge the gap between humanitarian and development actions and to provide "an overarching organizational scheme within which vulnerability, shocks, and heterogeneity of recovery pathways may be measured" [1]. Vulnerability and resilience analysis have been promised to help policy makers take earlier action to address emerging crises, better design and evaluate interventions, and better identify which individuals to target as part of those interventions.

Despite its emergence as a central narrative in international development, there is as yet no consensus on the definition of resilience, nor on its measurement. In fact, despite the considerable financial resources being channeled into resilience-building activities, resilience has not yet been empirically proven to be distinct from poverty and vulnerability. This study produces a framework in which poverty, vulnerability and resilience are defined as distinct dimensions of well-being, such that they can be measured independently.

We propose a set of indices to summarize resilience and vulnerability. They can be applied to analyze a variety of well-being outcomes (e.g. consumption-expenditure, undernutrition, etc.) and shocks (e.g. climate change, price volatility). A further advantage of the measures is that they are comparable across time and space, allowing us to compare vulnerability and resilience across countries or regions, or for the same country or region in different time periods. This report applies the methodology to the relationship between weather shocks (e.g. droughts, floods) and food consumption in Ethiopia.

2 DEFINITION

2.1 BROAD DEFINITION

The utility of "resilience" in designing and evaluating interventions depends largely upon how it is defined. The international development sector has proposed myriads of definitions for resilience. Emerging from the many definitions are at least two distinctive characteristics of resilience: (1) the capacity to withstand a shock and (2) the capacity to bounce back after a shock. The first can be understood as the absence of vulnerability, which essentially involves a normative goal of preventing individuals from falling into a poverty trap. The second is more dynamic; it is the ability of the system to recover to the original or an improved level of well-being. It is from these two characteristics that we see the crucial link between humanitarian assistance and broader development efforts [10-12].

Resilience thinking in development economics has largely benefited from the coping capacities literature, which developed out of the insight that individuals differ in their capacities to withstand shocks according to their risk management strategies. While *ex-ante* risk mitigating strategies seek to decrease the potential exposure to a hazard, *ex-post* risk coping strategies aim to decrease the effect of the hazard once it has struck [13]. Following the coping capacities literature, resilience is conceived of as a capacity [e.g. 14, 15, 16] with three components [17, 18], the first two of which are closely related to risk mitigating and risk coping strategies. *Absorptive capacities* concern the first characteristic of resilience: the ability to withstand a shock. *Adaptive capacities* concern the second: the ability to bounce back after the shock. *Transformative capacities* consist of policy approaches, such as scalable social protection schemes (e.g. The Productive Safety Net Program (PSNP) and the Pastoralist Areas Resilience Improvement and Market Expansion (PRIME) project in Ethiopia), which involve the ability to radically transform the socio-economic system to prevent future exposure to shocks.

From the literature, it is evident that there is little consensus on the definition of resilience, and the conceptual boundaries are fluid, with a tendency towards broad and eclectic frameworks that embrace multiple dimensions of relief and development. Resilience is a set of capacities demonstrated in multiple time periods (ex-post and ex-ante) and at multiple levels (individual, household, community, group). It is concerned with any manner of shock (both covariate and idiosyncratic) and well-being measure. It is long-term, integrated, cross-sectoral and applicable at multiple scales [19, 20]. This broad approach has gained

virtually universal acceptance for the resilience concept, as demonstrated by the vast amount of financial resources being channeled into resilience-building activities.

However, we are concerned that by blurring important distinctions, such as that between poverty, vulnerability and post-shock recovery, the broad definition of resilience does not lend itself to precise measurement and specific policy inference. At a minimum, a broad, multi-dimensional definition complicates our ability to link the measure to a specific Theory of Change for any intervention. At worst, this effectively makes resilience synonymous with any welfare improvement, thus making it a catch-all term for all positive objectives of a policy or project. This makes measurement, evaluation and impact attribution very difficult by suggesting that any intervention impacts resilience and offering no new insights compared to existing concepts.

2.2 NARROW DEFINITION

With an eye towards specific policy inference and impact attribution, we choose to adopt a narrow view of resilience, defining it within the most widely used framework for measuring well-being. The narrow view sees resilience as distinct from the already well articulated concepts of poverty (a snapshot of well-being at a particular point in time) and vulnerability (an ex-ante assessment of expected poverty). Within the narrow lens, the added value of resilience is its focus on dynamics: the poverty pathway over time. We therefore define and measure resilience as the speed of recovery after a shock. Within this framework, welfare can be addressed along three dimensions: eradicating poverty, alleviating vulnerability and building resilience. Each dimension is measurable in its own right and is associated with a specific set of policies, enabling policy makers to identify the right policy mix for a particular population group.

To distinguish between these dimensions, we refer to Box 1 on the following page, in which Plot A represents a poor household and Plot B represents a non-poor household.

Beyond serving as a general rallying cry to improve coordination between development and humanitarian players, does the resilience concept add substantively to our policy analysis toolkit? Specifically, does “resilience” add evaluative insight that is not already captured in the ample literature on poverty and vulnerability?

A direct benefit of taking the narrow view of resilience is that it allows for a clear and nuanced classification of households along each dimension of well-being and a clear identification of the set of appropriate interventions for supporting each dimension. Poverty can be addressed through long-term policies such as those that impact economic growth (e.g. macro policies and investment), redistribution (e.g. regular cash transfers, land reform), market policies and improved public services (e.g. education, healthcare). Policies to reduce vulnerability including a range of ex ante risk reduction strategies (e.g. drainage, irrigation, livelihood diversification), and ex post interventions (such as emergency handouts) that soften the immediate welfare impact of the shock. Resilience can be built through policies aimed at hastened recovery, such as public and private insurance, post-crisis recovery investments, and graduation systems for weaning people off relief assistance, as well as policies that build adaptive capacity. Furthermore, the narrow view of resilience lends itself more to monitoring and evaluation, as it offers a measurable outcome variable and a clear set of interventions that are likely to have a direct impact.

Box 1: Narrow definition of resilience

1. Poverty: Observed at a specific time period. A household is poor if its level of consumption is below a given reference point, such as an official poverty line.
    - For the poor household in Plot A, poverty in time period 1 is represented by distance ***A***.
    - The non-poor household in Plot B is above the poverty line in time period 1.
2. Vulnerability: An ex-ante, or forward-looking prediction of future poverty. Both households are expected to experience a shock in period 2; their vulnerability is represented by distance ***B***.
    - For the poor household, vulnerability is the difference between the initial level of consumption and post-shock consumption.
    - For the non-poor household, it is the difference between the poverty line and post-shock consumption.
3. Resilience: A dynamic assessment of how a household will react in the event of a shock. If a household takes a long time to recover, the household lacks resilience. Households who bounce back more quickly are resilient. This is represented by the line ***C***.
    - For both households, resilience is measured from the time period with lowest consumption to the time period in which the household has recovered to its pre-shock consumption level

2.3 APPROACHES TO MEASURING RESILIENCE

Two main estimation strategies are possible for resilience measurement. The first seeks to estimate resilience capacity directly (hereafter *resilience as capacity*). Under this method, resilient households have more capacities. The second approach aim to estimate the outcome of these capacities (hereafter *resilience as an outcome*). Under this approach, resilient households are those that recover more quickly. The important methodological distinction is that, in the *capacity* approach, the first step consists of constructing a capacity index, while, in the *outcome* approach, the first step consists of estimating the dynamics of well-being over time. In both approaches, the analyst can seek to identify what drives resilience.

Measurement strategies that seek to estimate *resilience capacity* directly include the Resilience Index Measurement and Analysis (RIMA) model developed at FAO [15, 21]; the DfID/Tango framework [22-24]; and the Oxfam methodology [25-27]. Resilience is defined as a composite index of a set of components, such as absorptive, adaptive and transformative capacity, each of which are unobserved and estimated using a subset of carefully selected variables [24]. A recent report from Tango has shown the applicability of the approach in an evaluation context [24]. Resilience-as-capacity measurement approaches tend to

rely heavily on principal component analysis: inside each index, built on unobservable characteristics, lays another index, also built on unobservable characteristics. Resilience is conceptually decomposed into many parts and then re-assembled by a multi-stage estimation.

The second estimation strategy views resilience as a dynamic property of well-being. Although a resilience index following the *resilience as outcome* approach has not yet been defined, several authors have taken an outcome-based approach to resilience, including Barrett and Constas [14]; the World Bank [28]; Di Falco and Chavas [29]; and the Tufts Livelihood Change over Time (LCOT) Model [30, 31]. Although they do not provide an explicit resilience index, Barrett and Constas [14] suggest that "such an approach would represent an intertemporal and probabilistic extension of the workhorse Foster–Greer–Thorbecke poverty measure to take into account the predictable path dynamics of well-being." We follow their hint for designing our resilience index.

A challenge to both approaches is the need for high frequency panel data in order to track well-being over time. Such data is rarely available and costly to collect. We propose a novel approach to circumvent this limitation, making the technique applicable to countries that collect data on well-being and living standards only intermittently.

3 THE MODEL AND INDICES

Following the *resilience as outcome* estimation strategy, the foundation of our model is the relationship between any risk process and the human outcome of interest over time. For illustrative purposes, we apply the model to the specific relationship between the severity of the weather shock and the change in consumption over time, although the method could equally be applied to other types of risk as well as other health or economic outcomes. We rely on the Standardized Precipitation Evapotranspiration Index (SPEI)[2] [7] as the weather variable and food consumption as the well-being variable. Once the relationship between climate and consumption is clearly established, we can summarize the information in vulnerability and resilience indices in order to guide policy decisions. Essentially, the vulnerability indices summarize the climate-consumption dimension while the resilience indices summarize the time-consumption dimension. We provide a descriptive and graphical explanation of the indices herein, leaving the mathematical formulas in the appendices.

The following is a series of questions we would like to answer, along with the corresponding indices that will allow us to address them. Box 2 summarizes the indices.

- Will a household become poor in the event of a specific weather shock and, if so, how poor?
    - *Weather vulnerability index*
- What is the average drop in poverty caused by weather shocks?
    - *Climate vulnerability index*
- How quickly will a household will recover in the event of a specific weather shock?
    - *Weather resilience index*
- On average, how quickly does a household recover from weather shocks?
    - *Climate resilience index*

[2] SPEI is a measure of precipitation minus evapotranspiration. In other words, it is the value of the net balance of water in the ecosystem.

Box 2: Summary of indices

NAME	DESCRIPTION	POLICY USE
Weather Vulnerability	Weather-Induced Poverty Gap: Expected poverty due to a weather shock	Contingency Planning Early Warning
Climate Vulnerability	Climate-Induced Poverty Gap: SPEI probability-weighted weather vulnerability	Policy Targeting Long term regional allocation
Weather Resilience	Speed of Recovery: share of time before a next shock is expected to strike spent not recovering	Post Shock Recovery Planning Early Warning
Climate Resilience	Average Speed of Recovery: SPEI probability-weighted weather resilience	Policy Targeting Long Term Regional Allocation

Following a number of authors [32-38], we base our indices on the Foster-Greer-Thorbecke (FGT) class of poverty measures [39]. The FGT measures are simple, easy to understand and easily communicable, with straightforward interpretations. Similarly, they are already well integrated in policy design and analysis. As it is based on the FGT, our complete methodology includes four classes of indices. For simplicity, we present the main index from each class herein.

3.1 CLIMATE DIMENSION OF THE CLIMATE-CONSUMPTION MODEL FOR ESTIMATING VULNERABILITY

3.1.1 WEATHER SENSITIVITY

The model is grounded on the observation that most households in rural Sub-Saharan Africa are smallholders whose primary consumption comes from rain-fed subsistence agriculture and who have little or no surplus available for sale. As such, they are greatly affected by variations in the weather. We thus begin by simply plotting the relationship between SPEI (see Box 3) and consumption. The resulting curve, which we call the *climate-consumption curve*, follows an inverted-U shape, as depicted for two representative farmers in Figure 1. For both farmers, consumption is highest in conditions near normal or slightly moister than normal and drops in cases of excess moisture or drought.

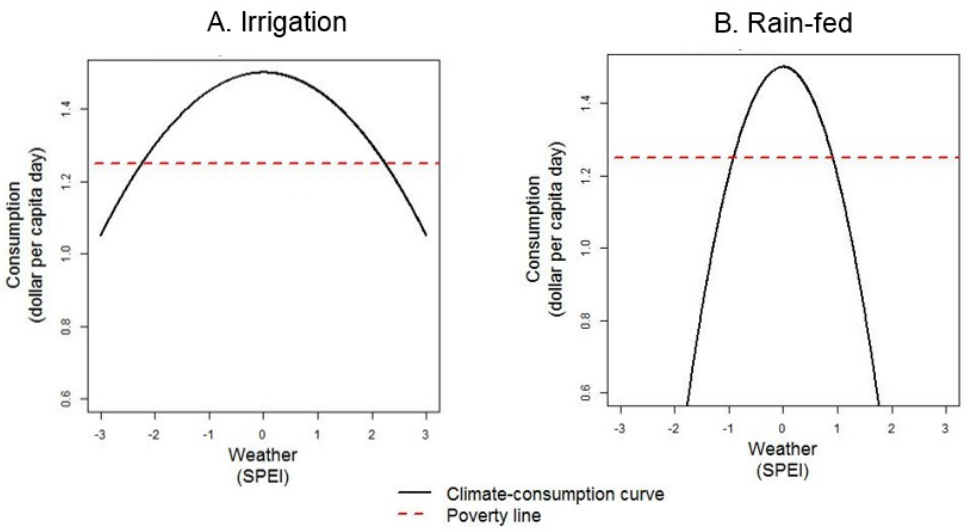
Box 3: SPEI

The SPEI is a local, standardized measure of the net balance of water in the ecosystem, measured as precipitation minus evapotranspiration. Table 1 presents an interpretation of various SPEI values. See Annex B for the derivation

Table 1: SPEI interpretation

SPEI VALUES	EXPECTED TO OCCUR AT MOST EVERY:
2.3	100 years
1.64	20 years
1.28	10 years
0.84	5 years
-0.50 <= SPEI <= 0.50	<5 years
-0.84	5 years
-1.28	10 years
-1.64	20 years
-2.3	100 years

Figure 1: Weather sensitivity



The vertical position of the climate-consumption line represents the overall poverty level. Higher curves represent less poor households, and lower curves represent poorer households. The climate-consumption curve's horizontal position represents the conditions in which consumption reaches its peak. Curves that are shifted to the right indicate that consumption peaks in moister-than-normal conditions; curves shifted to the left indicate that consumption peaks in drier-than-normal conditions. Curves that are centrally located indicate that consumption peaks during normal conditions.

The curvature of the climate-consumption line represents *weather sensitivity*. More steeply-curved lines represent households that are more sensitive to changes in the weather, while flatter lines represent households that are less sensitive. In Figure 1, Plot A represents a farmer with irrigated and well-drained farming plots, while plot B represents a farmer operating rain-fed plots. A small deviation from normal conditions will cause a large decline in consumption for the rain-fed farmer, who will quickly fall below the poverty line. Conversely, thanks to his or her flatter climate-consumption curve, it will take a large deviation from normal conditions for the farmer with irrigation to fall below the poverty line. The rain-fed farmer is thus more sensitive to variations in climate than the farmer with irrigation.

3.1.2 WEATHER VULNERABILITY INDEX

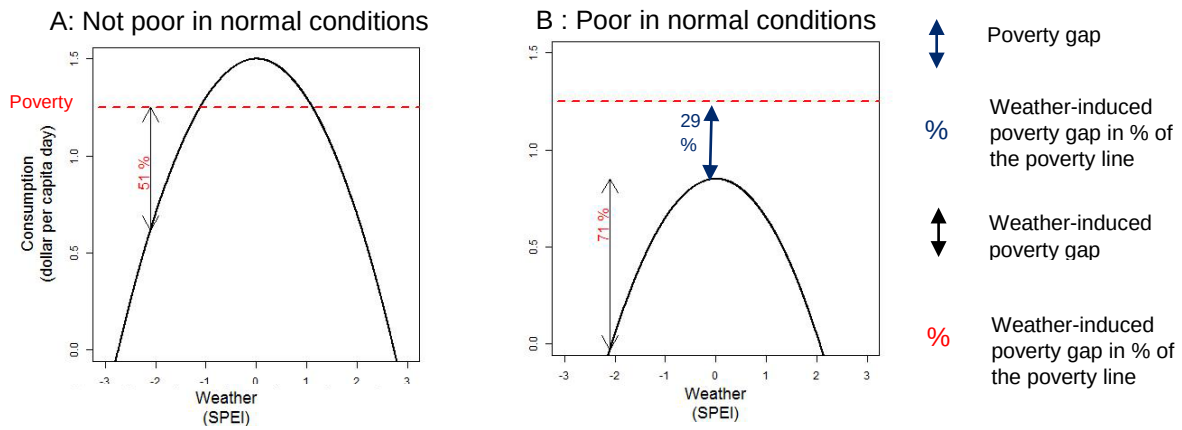
We rely on a household's weather sensitivity to determine its level of vulnerability, which is measured with respect to the poverty line. When we consider vulnerability to a given weather shock, we refer to *weather*-vulnerability, which is expected poverty *caused by a weather shock*. Our measure of weather vulnerability is the difference between expected FGT in normal conditions and expected FGT in adverse weather conditions, expressed as a percentage of the poverty line. Weather vulnerability is thus defined as the expected weather-induced poverty gap.

Note that our measure does not incorporate the poverty gap that a poor household will experience under normal conditions (i.e. chronic poverty gap). For instance, a waste picker in a large city has close to 100% chance of staying poor next year, regardless of the weather conditions that occur. His vulnerability to poverty in general is close to 100%. However, his vulnerability to poverty *caused by weather* conditions is close to zero. This is the reason we look at the difference in poverty between normal weather conditions and adverse weather conditions for the poor households.

Figure 2 shows the drought vulnerability scores for two households exposed to an extreme drought that is expected to recur only once in 50 years (SPEI = -2). Household A is not poor in normal conditions. However, in the event of a 50 years' return drought, it is expected to fall 51% below the poverty line. Its

drought vulnerability score is thus 51%. Household B experiences a 29% poverty gap in normal conditions. In the event of the drought, it is expected to fall to zero consumption. Therefore, its *weather-induced* poverty gap, and thus its drought vulnerability score, is 71%. The difference between the status-quo and the poverty line, i.e. poverty in normal weather conditions, is not taken into account in the calculation of the index because it is not caused by the weather shock.

Figure 2: Weather vulnerability indices

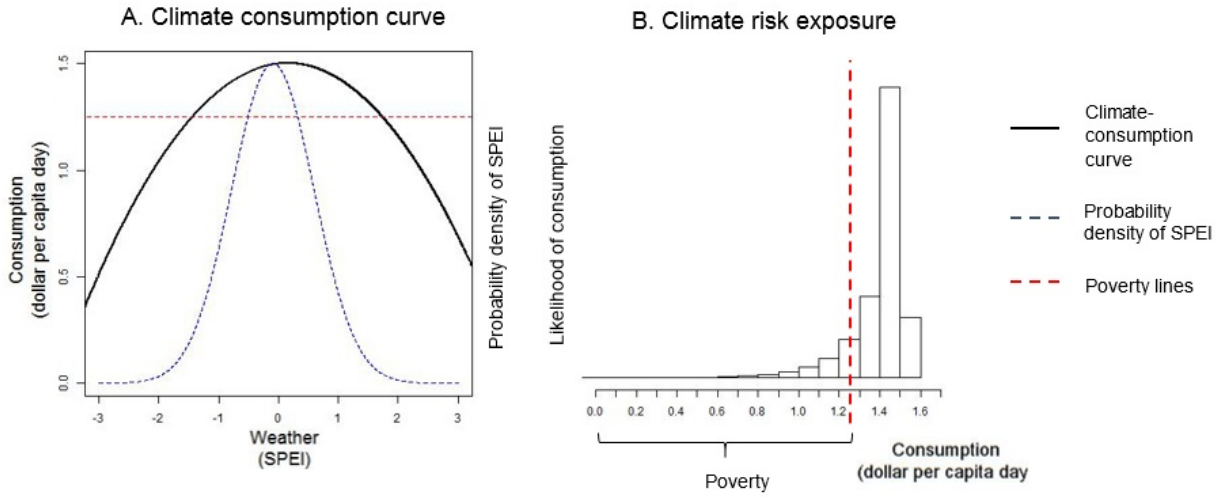


A household's weather sensitivity, and thus also its weather vulnerability, is determined by its absorptive capacity. A household with greater absorptive capacity, such as the farmer with irrigation described above, can better withstand a shock; it is less vulnerable. Conversely, a household with low levels of absorptive capacity, such as the farmer with rain-fed plots, will not be able to withstand a shock, making it more vulnerable. Vulnerability is therefore the outcome resulting from a lack of absorptive capacity.

3.1.3 CLIMATE RISK EXPOSURE

When we consider vulnerability under all possible weather scenarios, we refer to *climate vulnerability*. To measure it, we need to have a sense of the entire distribution of possible consumption levels given the local climate. The advantage of using the SPEI, or any other weather index with a known statistical distribution, is that it we can probability weight the climate-consumption curve to identify a household's *climate risk exposure*, or likelihood of various consumption levels. Figure 3 illustrates the method.

Figure 3: Low climate risk exposure

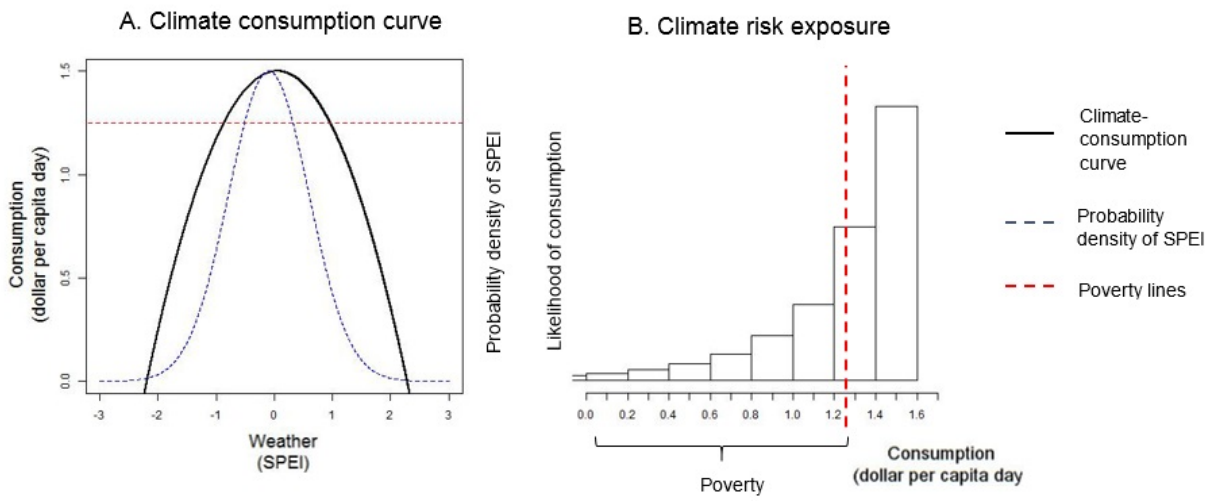


In Plot A, we overlay the household's climate-consumption curve with the probability density distribution of the SPEI. Weather-consumption scenarios occurring around normal weather conditions (generally the highest levels of consumption) are most likely because the corresponding SPEI values are more likely. Similarly, weather-consumption scenarios occurring in extreme weather scenarios (the lowest levels of consumption) are relatively unlikely, as the corresponding SPEI values are unlikely.

We use the SPEI distribution to assign a probability weight to each weather-consumption scenario, such that we can calculate the household's *climate risk exposure,* represented in Plot B. Consumption is now displayed along the x-axis, while the probability of that level of consumption is displayed on the y-axis. Consumption levels with higher bars are more likely to occur than consumption levels with lower bars. The graph thus represents the level of climate risk that the household faces.

A household facing low levels of climate risk, like the one represented in Figure 3 will exhibit high bars on the right-hand side of the poverty line, reflecting a high likelihood that the household will experience consumption above the poverty line in the following year. Conversely, as illustrated in Figure 4**,** a household facing high levels of climate risk will exhibit more/higher bars on the left-hand side of the poverty line, reflecting a greater likelihood that it will experience some level of consumption below the poverty line the following year.

Figure 4: High climate risk exposure

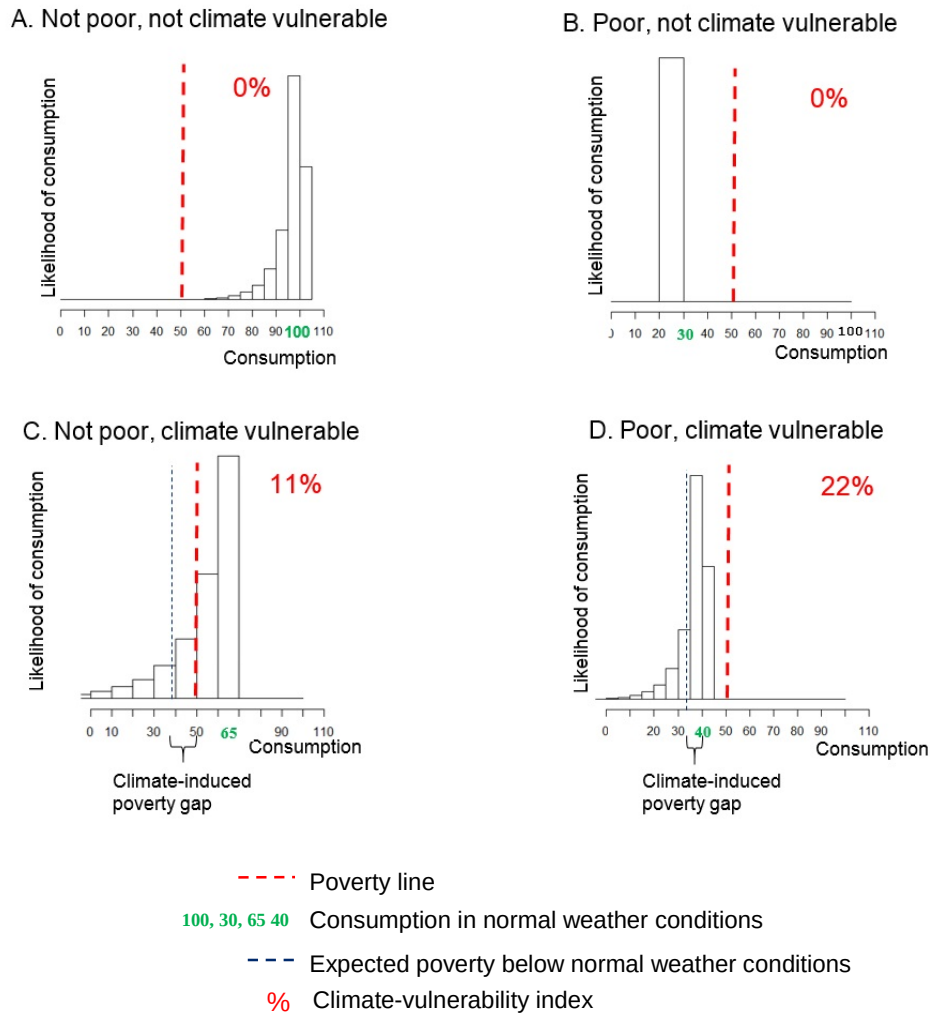


3.1.4 CLIMATE VULNERABILITY INDEX

The climate vulnerability index is simply the average weather-induced poverty gap, expressed as a percent of the poverty line. It answers the following question: if a weather shock occurs, how much is the poverty gap expected to increase next year? The distinction between the weather vulnerability index presented in 3.1.2 and the climate vulnerability index presented here is that for the climate vulnerability index, we do not specify the type of shock (e.g. a 10 years return drought). Rather, we want to know what might happen next year, on average, given *any* deviation from normal weather conditions.

This example shows that there are two ways for an individual to not be climate vulnerable, represented in Plots A and B in Box 4.

Box 4: Climate vulnerability index



In plot D, the poverty gap under normal conditions (the difference between the green label and the red dotted line) is not caused by deviations from normal weather conditions. The climate-induced poverty gap is the difference between consumption under normal weather conditions, labelled in green, and expected consumption under adverse weather conditions, denoted by the black dotted line. The index only accounts for the climate-induced portion of the poverty gap. It is expressed as a percentage of the poverty line.

The individual depicted in Plot A is non-poor, and although her consumption may vary with weather, it never falls below the poverty line. We can imagine her climate-consumption line, which would be curved but always remain above the poverty line. Plot A shows her climate risk exposure graph, which we can draw after probability-weighting her climate-consumption curve by the SPEI. All of the bars lay to the right-hand side of the poverty line. Therefore, her climate vulnerability score is 0%; she is not climate vulnerable.

Conversely, Plot B depicts an individual similar to the waste picker in the example above. He is poor but his consumption does not vary with weather. We can imagine his climate-consumption line, which would be flat and lay near zero consumption. Once this is weighted by the SPEI, we can calculate his climate risk exposure, represented in Plot B. Because he is poor, it lays to the left of the poverty line. Because his

expected consumption does not vary, there is only one bar in the graph. As a result, his climate vulnerability score is 0%. He is chronically poor but not climate vulnerable.

Of course, most households do not fit either of these two extreme cases. For instance, the individual represented in Plot C is non-poor in normal weather conditions but sensitive to weather variation. Her climate-consumption line would peak above the poverty line in conditions near normal but fall below the poverty line in extreme conditions. The histogram of her climate risk exposure, in Plot C, thus crosses the poverty line. If her average climate risk exposure were to fall to the right of the poverty line, she would not be climate vulnerable. However, because her average climate risk exposure falls to the left of the poverty line, she is climate vulnerable. The degree of vulnerability is calculated as the percent difference between the average of her climate risk exposure and the poverty line. For this particular individual, it is 11%. She is not chronically poor, but she is climate vulnerable.

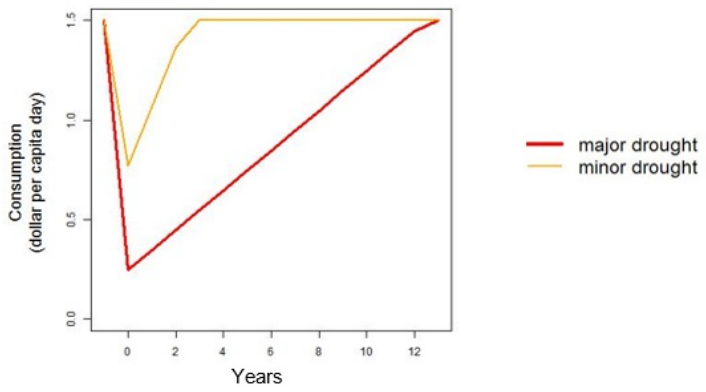
Plot D represents an individual who is poor under normal weather conditions and sensitive to weather variation. His climate-consumption line would peak below the poverty line and exhibit a curved shape. His climate risk exposure histogram lies completely below the poverty line. Because he is already poor, it is not possible that he will become non-poor as a result of the shock. Taking the percent difference between the average poverty gap under adverse conditions and the poverty gap under normal conditions, we can calculate his climate vulnerability at 22%. It is important to keep in mind that this value represents his climate-induced poverty gap, not his total poverty gap. If we are interested in estimating his total expected poverty gap, we simply add his poverty gap under normal conditions to his climate-induced poverty gap presented here. This individual is both chronically poor and climate vulnerable.

3.2 TIME DIMENSION OF THE CLIMATE-CONSUMPTION MODEL FOR ESTIMATING RESILIENCE

3.2.1 POST-SHOCK CONSUMPTION PATH

To broaden the scope of the analysis to resilience, we to need to see how consumption changes over time, from before the shock until the household has recovered. We therefore need to provide a dynamic extension of the framework above. Figure 5 presents two consumption paths. In the preceding section, we focused on the post-shock drop in consumption. In this section, we are predominantly concerned with how the household's consumption trajectory changes *after* its consumption falls.

Figure 5: Recovery paths



A household's recovery path is likely to depend on the severity of the weather shock that it experiences. We would expect the slope of the recovery trajectory to be steeper after a small shock than after a large shock, as households tend to employ different coping strategies depending on the severity of the shock. For instance, in the event of a minor shock, the household may have enough savings to nearly smooth its consumption, thus experiencing only a minor blip in consumption as a result of the shock. However, the household may not have enough savings to smooth consumption in the case of a large shock. Rather, it

may be forced to rely on last-resort coping strategies such as selling off productive assets. Such irreversible coping strategies tend to result in a much lower rate of recovery, as represented in Figure 5.

Recovery paths are also likely to differ between households experiencing the same shock, as each household begins with a different asset stock and utilizes different coping mechanisms. For instance, some households will be able to recover more quickly than others because they can count on help from relatives or because they are able to draw down their savings in order to re-invest in farm activities. The capacities approach can shed light on the household characteristics that are most likely to hasten recovery. With high frequency, long series panel data, we could potentially assess the relationship between specific capacities and recovery rates. This would allow for the definition of rational weighting strategies for indices as well as for more precise identification of the capacity investments that are most likely to hasten recovery.

The narrow view of resilience focuses on the duration and shape of the recovery path. As these two examples highlight, a household's recovery path, and thus also its resilience, is determined by its adaptive capacity. A household with greater adaptive capacity will exhibit greater resilience (quicker recovery), while a household with low levels of adaptive capacity will not exhibit resilience (slow or no recovery).

3.2.2 WEATHER RESILIENCE INDEX

The narrow definition of resilience is fundamentally relational: households recover quickly or slowly relative to a given benchmark or baseline measure. To develop a resilience index, we must therefore determine a resilience threshold which defines the "breaking point" between a household that is "resilient" and one that is "not resilient".

We select five years as the resilience threshold for several reasons. First, selecting a discrete value allows for temporal comparison of resilience among shocks of various sizes. Second, five years is roughly the minimum return period of weather events considered abnormally dry or wet (SPEI = ± 0.79, i.e. a return period of 4.7 years). Thus, selecting five years as the threshold value allows us to consider the fact that shocks are recurrent. Under this definition, a household with a positive resilience score is likely to be able to recover to its initial baseline value of consumption before the next shock strikes. However, a household with a negative resilience score is at risk of being set on a downward spiraling trajectory, as it is likely to be hit by a second shock before it has fully recovered from the first.

With the recovery threshold set at 5 years, the weather resilience index is defined according to a simple formula:

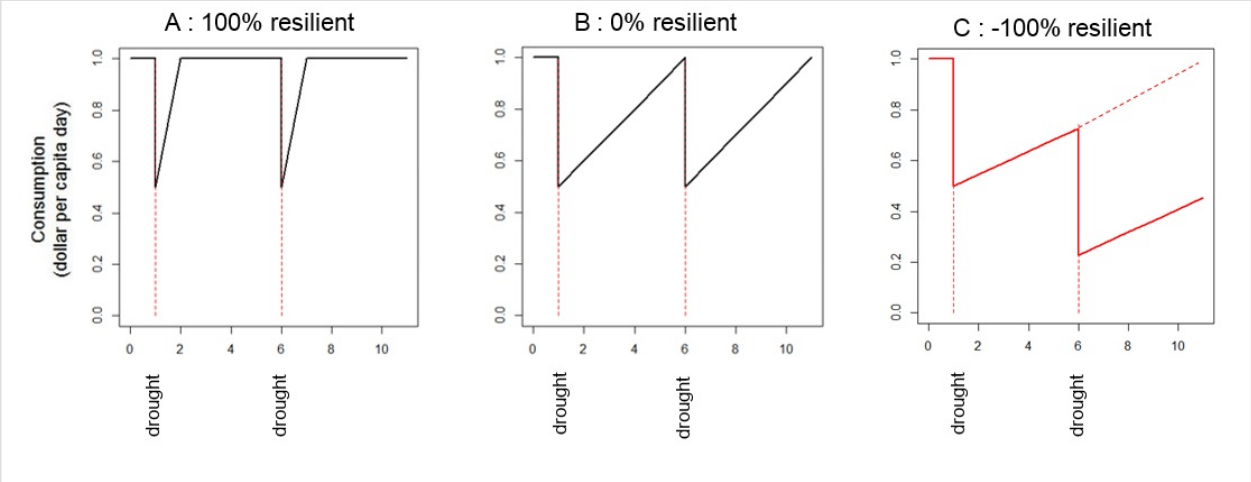
$$\frac{5 - recovery\ duration}{5 - 1} * 100$$

We bind negative resilience to -100% (9 year recovery). Households taking more than 9 years to recover therefore receive a score of -100%[3].

Box 5 presents a graphical example and interpretation of weather resilience scores for three individuals.

[3] There are two reasons for this. First, if no bounds are imposed, households that are set on a downward trajectory path would receive a score of minus infinity, as they would never recover. Second, a score of 200% would mean that a household recovers in 18 years. However, current statistical tools and data do not allow for such long term estimates. By binding the resilience index, we ignore predictions made over more than 9 years.

Box 5: Weather resilience index



All three individuals begin with the same level of consumption in period 0. In period 1, they all experience a shock of equal magnitude, evidenced by the equal drop in consumption. They are thus equally vulnerable. However, their post-shock recovery durations are decidedly different; they are not equally resilient.

- Individual A immediately recovers to her pre-shock level consumption level in year 2. She is 100% resilient.
- Individual B recovers just before the shock strikes again in year 6. She is able to consistently, but barely, return to her original consumption level before dropping again. She is 0% resilient.
- Individual C takes longer to recover. Based on her recovery trajectory, if no second shock occurred, she would have recovered to her initial level of consumption in year 11, as shown by the dotted red line. Calculating the index, i.e. she is -100% resilient. Note that when the second drought occurs in period 6, she is has not been able to fully recover from the first one, and instead follows a downward spiraling trajectory, as demonstrated by the solid red line.

The weather resilience index has the advantages of being extremely intuitive, comparable across weather shocks, and independent from the vulnerability index. For instance, a score of 50% always means that a household will recover in three years, regardless of the severity of the shock and regardless of the initial fall in consumption. It can therefore be used to compare resilience between households. It can distinguish between slow and fast recovery. It can be easily aggregated across households. Finally, we can distinguish which households are likely to be set on a downward recovery path, as taking more than five years to recover implies a high likelihood of being hit by a second shock before returning to the initial consumption level.

3.2.3 CLIMATE RESILIENCE INDEX

Following Figure 5, we see that a household's expected recovery path in response to any given shock is unique. However, we can imagine an infinite number of recovery paths, one for every possible shock severity. In order to assess a household's resilience to the full range of possible shocks, we follow the same approach we took in calculating climate vulnerability. To consider resilience to all possible weather scenarios, we probability-weight the full set of possible recovery paths of each household according to the SPEI distribution. The climate resilience index is calculated as the average weather resilience index of each household.

- A score of 100% means that given the distribution of climate patterns, the household is, on average, likely to fully recover after one year.
- A score of 50% means that given the distribution of climate patterns, the household is, on average, likely to recover in three years.
- A score of 0% means that given the distribution of climate patterns, the household is, on average, likely to recover in five years.
- A score of -50% means that given the distribution of climate patterns, the household is, on average, likely to recover in seven years.
- A score of -100% means that given the distribution of climate patterns, the household is, on average, likely to recover in nine years or more

4 DATA

To estimate the indices, we employ household microeconomic and climate data to explore the relationship between weather and household food consumption. We use three microeconomic datasets from Ethiopia:

- Ethiopia Living Standards Measurement Study (LSMS, 2012)[4] [40];
- Ethiopian Nile Basin Climate Change Adaptation Dataset (ENBCCA, 2005, 2012) [41]; and
- Ethiopian Rural Household Survey (ERHS, 1994, 1999, 2004, 2009) [42].

Our main dependent variable, food consumption per day, is presented in Appendix A.

While we explore the use of the Normalized Difference Vegetation Index (NDVI) and Water Requirement Satisfaction Index (WRSI)[5], we quickly identify that the model fits best with a standardized climate index. We then explore the use of:

- a Standardized Precipitation Index (SPI) that we compute from the CHIRPS precipitation dataset [43] using the R package SPEI [44];
- the Standardized Precipitation Evapotranspiration Index computed by Beguería and Vicente Serrano provided in the SPEI base dataset (SPEI base) [45]; and
- a new SPEI variable that we compute from a new and higher resolution evapotranspiration dataset produced by NOAA and the CHIRPS precipitation dataset, again using the R package SPEI. We refer to the new SPEI variable as SPEI NOAA, as it is based on our calculation using the new NOAA evapotranspiration dataset.

Between the SPI and SPEI, we find that the SPEI produces more stable results. Although the SPEI NOAA offered the promise of higher resolution, it did not produce stable results with the LSMS dataset[6]. Because the SPEI base produces the most stable results, we rely on it for the bulk of our analysis.

The use of secondary data allows the methodology to be replicable, low-cost and implemented in situations in which primary data collection is not practical or possible. The time series climate data also allows for an assessment of actual weather patterns over a prolonged period of time, fully capturing the

[4] We conducted our analysis on two LSMS food consumption variables. At the start of this project, no food consumption variable was available with the dataset, so we calculated our own. However, toward the end of the study, the World Bank (WB) made their food consumption variable available. The distinction is that the WB variable was constructed using a conservative and careful approach that involved winsorizing the data, or replacing the high and low values with upper and lower bound thresholds. Comparatively, we began by cleaning imputation errors prior to winsorizing. After a comparison of the stability of estimates across the two datasets, we decided to rely on the WB consumption variable for the analysis.

[5] The WRSI used in this study is a *basket* WRSI computed by FAO AgrometShell software and accessed via the LEAP software: 'Crop baskets are used to create compound indices (i.e. indices which cover more than one crop). In a compound index, crops are weighted according to a percentage that reflects the number of hectares grown, tons produced, or any other weighting. Crop baskets are used to calculate "basket WRSI"' (Hoefsloot et al.2013),

[6] The instability of the SPEI NOAA can be seen particularly when comparing the Kimetrica and WB food consumption variables for the LSMS. While the climate variable produces the expected results with the Kimetrica consumption variable, it results in extreme values with the WB consumption variable.

incidence of multiple weather shocks in each location on an objective scale that is comparable across locations. Conversely, specialized surveys based on household responses may not observe shocks over the course of the survey period. Furthermore, in the case of specialized surveys, the definition of a shock is subjective and not strictly comparable across observations.

5 METHODS

We use two different estimation techniques in our analysis. The first involves using standard OLS regressions to estimate the climate dimension, or the single-period model. It can thus calculate vulnerability scores but not resilience scores. The second is a new technique called a distributed lag non-linear model (DLNM) [8, 9]. It can account for consumption dynamics, allowing us to estimate the multi-period model, calculating the climate and time dimensions simultaneously. While the DLNM can calculate both vulnerability and resilience scores, because it is such a novel technique, we estimate it alongside the OLS model in order to compare the resulting vulnerability scores.

The OLS model involves a simple regression of SPEI and squared SPEI on food consumption. For the cross-sectional dataset (LSMS), we add a set of control variables. For the panel datasets (ERHS and ENBCCA), we include household fixed effects and time dummies along with the set of controls. The estimated parameters determine the curvature and horizontal location of the climate-consumption line and are used in the calculation of the weather and climate vulnerability scores.

The DLNM, developed by Gasparrini et al. [8, 9] uses an advanced mathematical technique to develop a variable that incorporates both the climate and time dimensions simultaneously. The model is then estimated using standard OLS regression. Ultimately, the model can estimate a three dimensional surface that shows how the climate-consumption curve evolves over time, allowing us to derive separate vulnerability and resilience indices.

The DLNM relies on weather data for estimating consumption dynamics. It uses the relationship between the weather events in the previous years and current consumption to predict consumption in the coming years given current weather conditions. In other words, by understanding how past weather events have affected current consumption, we can project forward to assess how current weather will affect future consumption over time. See Appendix D for an intuitive explanation of the DLNM model and Appendix E for the mathematical details. Interested readers are referred to [8].

Resilience measurement approaches generally require the use of microeconomic panel data, preferably of high frequency, to directly analyze consumption dynamics. There are thus several data challenges associated with resilience analysis. Panel data is costly to collect and the available datasets are collected at low frequency. For instance, the ERHS survey is conducted only once every five years. By focusing on climate dynamics rather than on consumption dynamics, the DLNM model does not *require* a panel dataset. Rather, the DLNM can be applied with one period of data if that is all that is available, allowing for resilience analysis to be possible in more contexts. To demonstrate how the DLNM model allows for resilience analysis with cross-sectional data, we calculate vulnerability and resilience indices using the Living Standards Measurement Survey herein.

Two additional benefits of the DLNM's reliance on climate data for dynamics are that it allows us to measure the cumulative effect of shocks, such that we can estimate the impact of repeated (or "double-bang") shocks, and it allows for more timely resilience assessments by being predictive rather than reactive. We demonstrate this by producing vulnerability and resilience forecasts.

Evidently, for both estimation techniques, the model requires geo-referenced household data with relatively large spatial coverage, making it unsuitable for small-scale projects where beneficiaries are all exposed to similar weather conditions and ideal for larger projects that are implemented at the regional or country level.

We highlight the fact that both model estimation techniques are based on household level data. When we estimate the relationship between consumption and weather, this relationship is estimated at the sample average. As explained in Section 3.1.1, the resulting climate-consumption curve has three distinct characteristics: its horizontal position, its vertical position and its curvature (weather sensitivity), and vulnerability is a function of each. While we estimate the climate-consumption curve's horizontal position and weather sensitivity at the sample average, by adding a set of control variables, we can allow the vertical position of the curve to vary according to a given household profile. For instance, by using quantile regressions, although the horizontal placement and curvature of the households' climate-consumption curves will be stable across socio-economic groups, the vertical location of the curves will vary, such that we can estimate average weather and climate vulnerability scores for households with different poverty levels. For instance, rich households' climate-consumption curves will lie far above the poverty line, such that it will be less likely to fall into poverty compared with a household whose peak consumption lies just above the poverty line. Furthermore, by allowing the regression coefficients to vary spatially, we can let all dimensions of the climate-consumption curves vary across the geography, such that we can obtain estimates of local vulnerability.

6 RESULTS

6.1 STABILITY OF RESULTS ACROSS DATASETS

6.1.1 CHOICE OF THE WEATHER VARIABLE AND STABILITY OF RESULTS

We began by looking for the best weather variable to explain consumption. We first compared the results obtained with the Water Resource Satisfaction Index (WRSI), the Normalized Deviation Vegetation Index (NDVI), the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI). We tested two SPEI models: the SPEI base and the SPEI NOAA. We ran the comparison on the LSMS dataset because of its wide geographical coverage. For each variable, we estimated two specifications: one with only the weather variable, regional and agro-ecological dummies and one with an added set of control variables (for a list of controls, see Table 5). The best results, both in terms of the explanatory power (R-squared) and the precision of the estimates (p-values), were obtained with the SPI and the two SPEI variables. Table 3 shows the results.

We then tested the stability of the results obtained with the SPI and the two SPEI variables over the three microeconomic datasets (ERHS, ENBCCA and the LSMS). Seven alternative model specifications for each microeconomic dataset were tried, beginning with no controls and subsequently adding sets of control variables. All climate-consumption dataset combinations and specifications tested are summarized in Table 2.

Table 2: Stability of results across climate datasets

DATASET	SPECIFICATION	WRSI	NDVI	SPI	SPEI BASE	SPEI NOAA-KIMETRICA
LSMS Only	1. No controls	X	X	X	X	X
	2. All controls	X	X	X	X	X
LSMS, ERHS and ENBCCA	1. No controls			X	X	X
	2. Socio-demographic characteristics			X	X	X
	3. 2 + farm characteristics			X	X	X
	4. 3 + access to services			X	X	X
	5. 4 + shocks			X	X	X
	6. 5 + aid			X	X	X
	7. 6 + year (ENBCCA & ERHS) or region (LSMS) dummies			X	X	X

Figure 6 presents the comparison between the SPI, SPEI base and SPEI NOAA regressions across the three microeconomic datasets, without control variables. The majority of the dataset combinations produce stable results, as demonstrated by the consistent upside-down U-shaped curve. In most cases, peak consumption is reached under normal conditions. The first exception is for the ERHS dataset, which shows peak consumption reached in conditions with a SPEI value slightly higher than normal.

The primary anomaly in the table is the LSMS / SPEI NOAA dataset combination. Although the SPEI NOAA has a better spatial resolution than the SPEI, unfortunately its results were not stable for the LSMS dataset, as demonstrated by the U-shaped curve. As a result of this analysis, we determined that more work is required on the new SPEI NOAA dataset before it can be used within this framework.

Between the SPI and SPEI base, the latter provided the most stable results across all three microeconomic datasets.

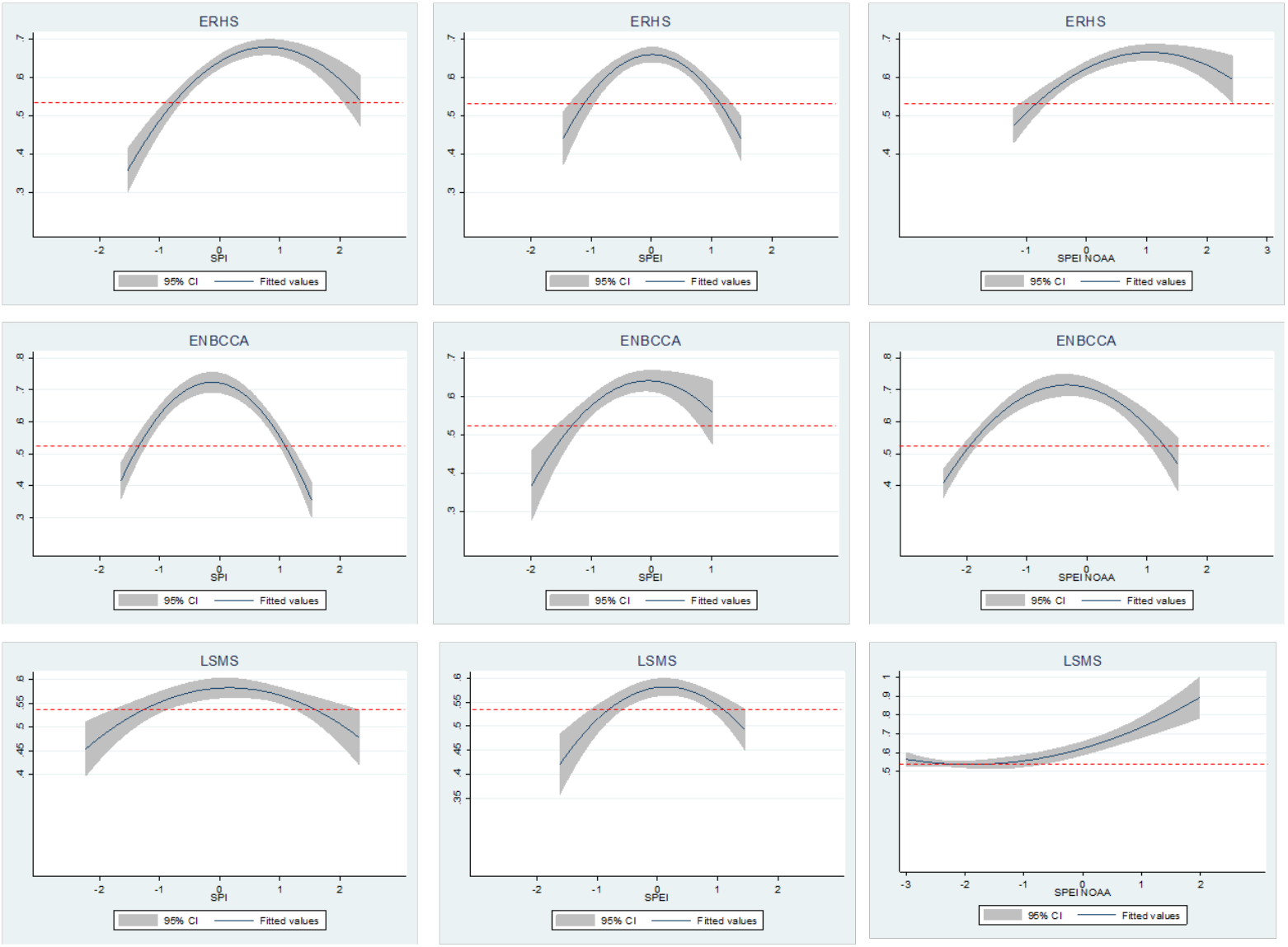
Table 3 shows that the curves produced from the SPI dataset vary across the household surveys. The ERHS curve is shifted to the right, the ENBBCA curve is centrally located and sharply curved, and the LSMS curve is quite flat. Conversely, the curves produced from the SPEI base are relatively consistent across datasets.

Table 3: Comparison of WRSI, NDVI, SPI, SPEI base on the LSMS datasets

FOOD CONSUMPTION PER CAPITA PER DAY	WRSI MEHER		WRSI BELG		NDVI: DEVIATION FROM LONG-TERM MEAN		SPI		SPEI	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Weather Index	-0.04	0.01	0.03*	0.04**	0.12	0.17	0.03*	0.01	-0.03	-0.03
	(0.09)	(0.09)	(0.02)	(0.02)	(0.16)	(0.15)	(0.01)	(0.01)	(0.03)	(0.03)
Weather Index^2							-0.03**	-0.03***	-0.09***	-0.08***
							(0.01)	(0.01)	(0.02)	(0.02)
Regions	X	X	X	X	X	X	X	X	X	X
AEZ	X	X	X	X	X	X	X	X	X	X
Controls		X		X		X		X		X
Observations	3266	3266	1087	1087	3679	3686	3679	3684	3681	3686
R^2	0.074	0.196	0.106	0.248	0.079	0.202	0.090	0.210	0.093	0.208

The WRSI was via the LEAP software from FAO [46]. It is as *basket* WRSI for the two main rainy season: 'Crop baskets are used to create compound indices (i.e. indices which cover more than one crop). In a compound index, crops are weighted according to a percentage that reflects the number of hectares grown, tons produced, or any other weighting. Crop baskets are used to calculate "basket WRSI" [47]. The sample size vary a lot between the WRSI indices because not all areas receives Meher or Belg rains. The NDVI data comes from the eModis dataset [48] and accessed via the FEWS NET website. The SPI is calculated with precipitation data from the CHIRPS dataset over the period 1981-2014 [43] with the SPEI software [44]. The SPEI is downloaded from the SPEI base dataset [45].

Figure 6: Food consumption per capita (USD/day) as a function of SPI, SPEI base and SPEI NOAA



We present a subset of the regression results in Table 4, in which model (1) is the specification without controls and model (2) is the specification with all of the controls. “Weather index” refers to the corresponding climate variable (SPI and SPEI base) listed in the columns for each dataset. The coefficient on the weather index is suggestive of the left-right position of the climate-consumption line, while the coefficient on the squared weather index is indicative of the curvature of weather sensitivity. Though not presented in this table for the sake of brevity, the coefficients on the control variables place the climate-consumption curve vertically.

In examining the regression results, we are primarily interested in obtaining a precise and stable estimate of weather sensitivity. Stability is assessed by looking for consistency in the coefficients of the weather variables between the model with controls and the model without controls (see Table 5 for the list of controls). The SPEI base provides the most stable results for all three microeconomic datasets. The effect of the SPEI base is not a statistical artifact caused by heterogeneity across agro-ecological zones and regions, as we controlled for these by adding agro-ecological zone dummy variables in the LSMS regression and fixed effects in the ENBCCA and ERHS regressions.

Precision is gauged by the statistical significance of the estimates. This is displayed by the number of stars on each coefficient. Again, the SPEI provides the most significant results for the three datasets: we can reject the null-hypothesis that the SPEI has no effect on consumption at the 99% confidence level in all cases. This means that despite the relatively low resolution of the SPEI (0.5 degrees long/lat), the microeconomic surveys are distributed on a sufficiently large area to allow simple OLS regression to pick up the effect of the variation in SPEI on consumption.

We do note that the R-squared values for the model with no controls (specification 1 in Table 4) are quite low: below 6 percent for each of the dataset combinations. However, this should not be a concern. The rounds we used for the ERHS were collected every five years, while seven years separate the two rounds of the ENBCCA panels. It is therefore no surprise to find that only five percent of the variation in consumption is explained by the SPEI, as many factors other than weather drive variation in consumption in the sample (e.g. socio-demographic and farm characteristics, regional differences). Once we add the full set of control variables, the R-squared increases to 15-30 percent depending on the dataset, meaning that the combination of weather and all of the controls explains 15-30 percent of consumption variation.

Table 4: Stability of results across microeconomic datasets

CONSUMPTION	ERHS				ENBCCA				LSMS			
	SPI		SPEI Base		SPI		SPEI Base		SPI		SPEI Base	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Weather Index	0.09***	0.01	0.00	0.07***	-0.03***	-0.06***	-0.01	0.02	0.02	0.01	0.02	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.06)	(0.01)	(0.01)	(0.02)	(0.03)
Weather Index^2	-0.06***	-0.00	-0.10***	-0.05***	-0.13***	-0.15***	-0.07***	-0.11***	-0.02	-0.03***	-0.06***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.04)	(0.01)	(0.01)	(0.02)	(0.02)
HH Fixed Effects		X		X		X		X				
Controls		X		X		X		X		X		X
Observations	4961	4945	4961	4945	1888	1888	1888	1888	3679	3684	3680	3686
R^2	0.017	0.145	0.010	0.151	0.056	0.295	0.014	0.290	0.007	0.210	0.013	0.208
Max at:	.8	1.14	.01	.66	-.13	-.18	-.05	.11	0.02	0.01	0.02	-0.03

Standard errors in parentheses (robust to error clusterization at the Woreda level)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The R-squared in models (1) refer to the overall R-squared, i.e. the share of overall variation in consumption explained by the regression. For model (2) of the ENBCCA and the ERHS, the R-squared values presented are the within R-squared as household fixed effects are used. For model 2 of the LSMS, the R-squared presented is the overall variation in consumption explained by SPEI.

SPEI: SPEI base dataset
SPI: Computed with the CHIRPS dataset

Table 5: List of controls

CONTROLS	
ERHS (1994, 1999, 2004, 2009)	
Socio-Demographics	female headed household [D], age of household head, completed primary education [D], households size in adult equivalent, off-farm job[D].
Farm Characteristics	total number of livestock expressed in tropical livestock units, land size main crops (ha), land flat [D], land with good soil [D].
Year Dummies	
ENBCCA (2005, 2012)	
Socio-Demographics	female headed household [D], age of household head, completed primary education [D], household size in adult equivalent, off-farm job [D].
Farm Characteristics	total number of livestock expressed in tropical livestock units, farmed area (ha), all plots are flat [D], erosion on some plots [D], all plots are highly fertile [D], fertilizers [D], preventive measures (pesticide, herbicide or fungicide) [D], improved seeds [D].
Access to Services	remote from selling market (>40km)[D], remote from input market (>12km)[D], access to electricity [D], access to telephone [D], access to secondary school [D], access to medical center [D], advice from extension workers [D].
Shocks	climate shock (drought, flood, hailstorm, landslide or fire) [D].
Aid	food/other aid received in the past 12 months [D]
Year Dummies	
LSMS (2012)	
Socio-Demographics	female headed household [D], age of household head, completed primary education [D], households size in adult equivalent, off-farm job[D].
Farm Characteristics	total number of livestock used for agricultural purposes expressed as TLU, farmed area (ha), all plots are flat[D], at least one plot is irrigated[D], at least one plot is prevented from erosion[D], at least one plot is fertilized[D], at least some seeds are improved[D], at least one plot receives preventative measures[D] (pesticides, herbicides, fungicide).
Access to Services	access to credit service[D], access to advisory service[D], participate in an extension program[D], remote from road[D], remote from market[D].
Shocks	food price increase or fall, or input price increase[D], crop or livestock damage or loss[D]
Aid	received remittances[D], received labor or non-labor assistance from PSNP in the last 12 months[D], received non-PSNP assistance in the last 12 months[D]
Agro-Ecological Zones	

[D] dummy variable (yes/no)

6.1.2 VULNERABILITY INDICES WITH THE STANDARD MODEL

The model can be used to calculate weather and climate vulnerability indices for the average household, as well as for poor and non-poor sub-groups. For poor households (those who are below the poverty line in normal conditions), vulnerability indices can be directly computed from the coefficients in the regression output from the standard OLS model (Table 4).

The key parameter is the coefficient on the SPEI squared, which gives a sense of the weather sensitivity of the household. By multiplying this coefficient by -2, we can approximate the average climate vulnerability index for poor households[7]. If the coefficient on the SPEI in levels (i.e. not squared) is not significant, we can also approximate the weather vulnerability of a poor household to shocks of various severities. Most simply, to estimate the weather vulnerability of a poor household to a 10 years' return drought, we multiply the coefficient on the SPEI squared by 3.4[8]. Table 6 presents the climate and weather vulnerability indices for the three microeconomic datasets. Confidence intervals are listed in parentheses[9].

Table 6: Climate and weather vulnerability scores for chronically poor households

SURVEY[10]	CLIMATE VULNERABILITY INDEX	WEATHER VULNERABILITY INDEX (to 10 years' return drought)
ENBCCA	22% (8%, 34%)	37% (14%, 58%)
ERHS	10% (4%, 18%)	17% (14% to 28%)
LSMS	16% (6%, 26%)	27% (10% to 41%)

On average, climate vulnerability for a representative poor household in the ERHS sample is 10%. This means that weather shocks, on average, cause poor households to fall an additional 10% below the food poverty line. In the ENBCCA sample, climate vulnerability for poor households is 22% on average. For the LSMS survey, the climate vulnerability index for poor households is 16%.

For a drought of a magnitude expected to occur every 10 years at maximum, the weather vulnerability index for poor households is 37% in the ENBCCA sample, 27% in the LSMS sample and 17% in the ERHS sample. For the LSMS and ENBCCA samples, the weather vulnerability scores for excess flooding expected to occur at the same magnitude are equivalent to the drought-vulnerability scores. However, recalling from Section 6.1.1, the ERHS climate-consumption curve is not centered at zero. As such, the 10-years' return excess moisture vulnerability score for poor households is 8% (confidence interval: 4% to

[7] As the climate vulnerability index is the average drop in consumption below the poverty line expressed as a percentage of the poverty line set at 0.53, multiplying the SPEI coefficient by -2 is a good approximation of the climate vulnerability index.

[8] The SPEI value corresponding to a drought of a magnitude expected to occur every 10 years is -1.28. As the SPEI is squared, by taking $-1.28^2 \approx 1.7$ and multiplying by the coefficient on $SPEI^2$, one can calculate the effect of a 10 years' return drought on consumption. Finally, by dividing by the poverty line, one can calculate the effect expressed as a percentage of the poverty line. As the poverty line is set at 0.53, multiplying the coefficient by $1.7 * 2 = 3.4$ gives the approximate effect of a drought expressed in percentage of the poverty line.

[9] The 95% confidence intervals for the LSMS and the ENBCCA indices are directly taken from the SPEI squared coefficient estimates from the regression results. For the ERHS, as the SPEI in levels is significant, a non-linear least squares panel regression was fitted by first demeaning all of the variables and then using the –nl– command from STATA. The confidence interval was then obtained by using the –margins– command to estimate the marginal effect of SPEI at -1.28. The marginal effect was then inflated by a factor of 1.28 for the drought and deflated the same factor for excess moisture. An alternative way of calculating the confidence interval would be to estimate the standard error by using the standard deviation of the bootstrapped predicted values at SPEI = -1.28.

[10] The LSMS indices reflect the expected change in consumption over a one year period. Because of the panel structure of and the use of fixed effects with the ENBCCA and ERHS datasets, these indices reflect the change in consumption caused by a weather shock for poor households over a seven and five year period, respectively.

12%). Comparing the two 10-year weather vulnerability scores, we see that poor ERHS households are less vulnerable to excess moisture than they are to drought.

These findings show some variation in weather and climate vulnerability across surveys, which is likely due to the surveys' heterogeneous spatial and temporal coverage. We will investigate this in more depth in Section 6.3.2.

6.1.3 RESULTS WITH THE DLNM MODEL

The DLNM model provides two types of information: how much variation in weather conditions in a given year affects consumption (the exposure relationship), and how this effect varies over time (the lag structure of the effect). It therefore increases the complexity of the analysis.

Based on the results from the standard OLS model, we assumed that the relationship between SPEI and consumption is quadratic and centered at zero at any given time. In terms of the lag structure, we accounted for the history of weather events for each household up to 15 years in the past. The most stable results were obtained with a decay function in which the effect of weather was allowed to decline over time, as would be expected. We then tailored the lag decay function parameter according to the results of a series of Aikake Information Criteria (AIC) tests [8]. Results are reported in Annex E

Results for the LSMS are displayed in Figure 7. The vertical axis shows the effect on consumption. Plot A shows the familiar inverted climate-consumption curve. Because the curve was constrained to be centered at a SPEI value of zero, any deviation from normal conditions causes a drop in consumption. Plot B shows the recovery path of an average household hit by a 10 years' return drought in time period 0. The bulk of the shock is felt in period 0, with a decline in food consumption equal to approximately five cents per capita per day. It is able to recover in about four years. Plot C illustrates the overall results of the DLNM model, which simultaneously estimates sensitivity (the climate-consumption curve represented in Plot A) and recovery trajectories for all possible weather shocks (such as the recovery path for a 10 year drought represented in Plot B). The DLNM can compute all of the indices introduced in Section **0**. Furthermore, it can model the cumulative effect of repetitive shocks and forecast future consumption trajectories, which we will illustrate in 6.3.1.

Figure 7: DLNM results, LSMS dataset

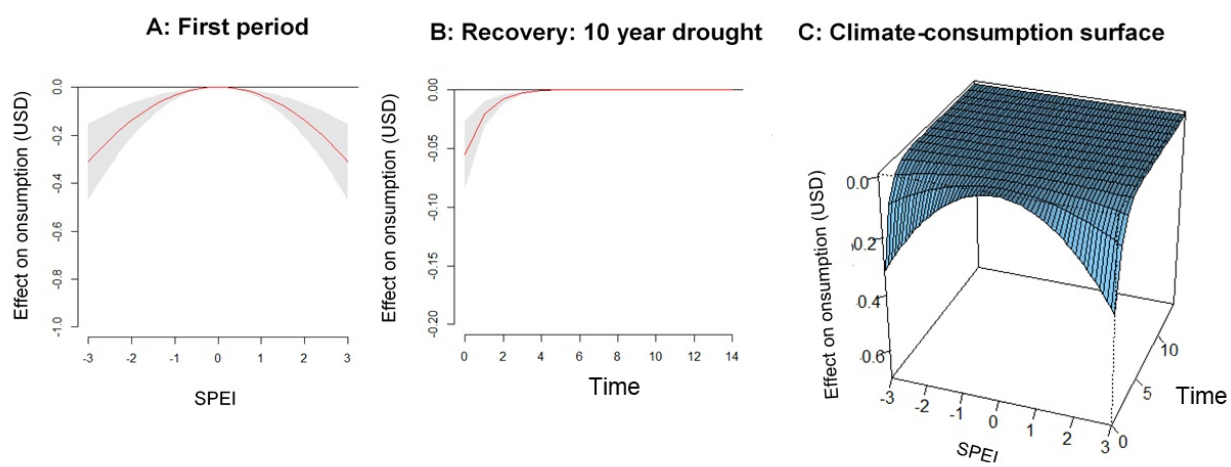
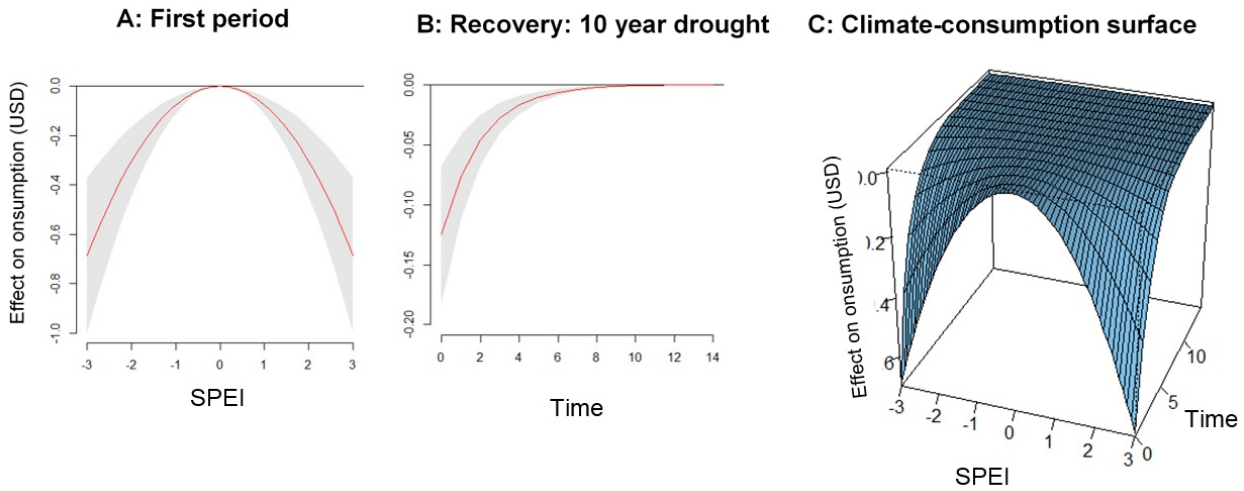


Figure 8 shows the results for the ERHS. We see that the communities in the ERHS sample are more weather sensitive than those in the LSMS, as shown by the steeper curvature of the climate-consumption line and the lower starting point of the recovery path. It also takes ERHS communities longer to recover from a 10 year return drought than those in the LSMS.

Figure 8: DLNM results, ERHS dataset



Finally, Figure 9 shows the results obtained with the ENBCCA dataset. The climate-consumption curves for the ERHS and ENBCCA are quite similar, and therefore, the initial drop in consumption resulting from a 10-year drought is of similar magnitude. However, the ENBCCA villages recover more quickly. This suggests that heterogeneous resilience and vulnerability profiles can co-exist.

Figure 9: DLNM results, ENBCCA dataset

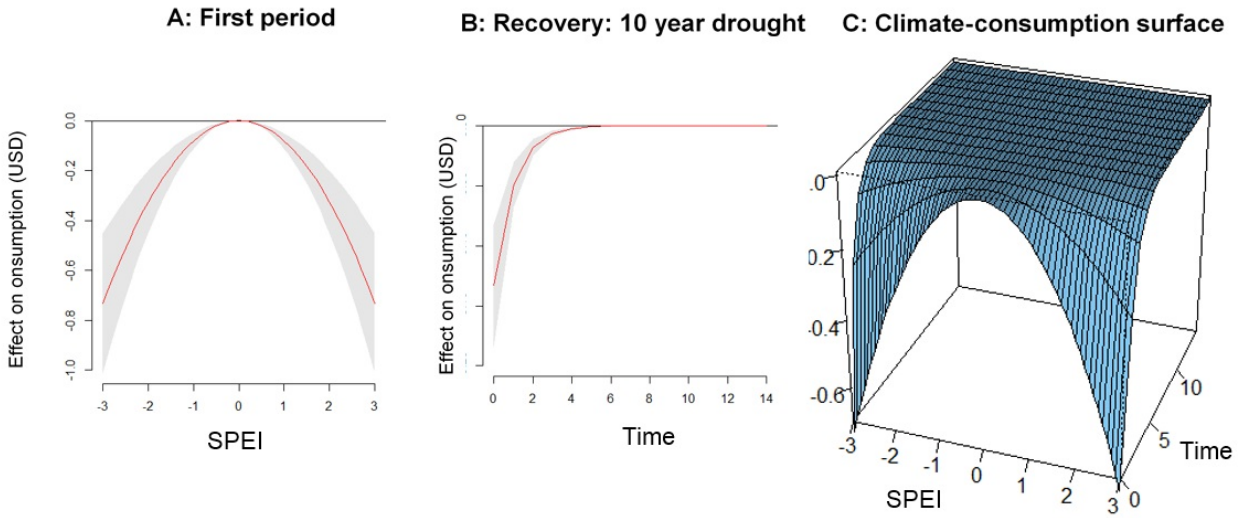


Table 7 summarizes the weather vulnerability, climate vulnerability and weather resilience scores across the datasets, as calculated by the DLNM model. The vulnerability scores are close to those obtained with the standard OLS model and always within their confidence intervals.

Table 7: Vulnerability and resilience scores using multi-period model

	LSMS	ERHS	ENBCCA
Weather Vulnerability to 10-Year Return Drought	10% (5.2%, 16.2%)	23% (13%, 34%)	25% (16%, 35%)
Climate Vulnerability	7% (3%, 10%)	14% (8%, 21%)	15% (9.5%, 21%)
Weather Resilience to 10-year Return Drought[11]	25% (4 year recovery) (50%, 0%)	-75% (8 year recovery) (-100%, -50%)	0% (5 year recovery) (-25%, -25%)

Confidence intervals in parentheses

Further work is needed in order to compute the climate resilience index. There are two primary possible avenues to do so. The first begins by computing the average recovery times for SPEI intervals. These values could then be weighted according to the probability that a SPEI value falls into each interval. The second possibility would involve simulating recovery paths for various SPEI values according to a large number of draws from a standard normal distribution. The average recovery path would then provide the climate resilience index. Ideally, we would like to find an analytical expression for the climate resilience index in terms of the estimated parameters of the DLNM model.

6.2 IMPACT EVALUATION OF CLIMATE CHANGE ADAPTATION STRATEGIES

The goal of a vulnerability and resilience impact evaluation is to answer the following question: does the intervention have an effect on vulnerability and resilience to weather shocks? If so, then program exposure should imply an improvement in the vulnerability and resilience measures for beneficiaries relative to non-beneficiaries. To address this question using our standard OLS model, we must interact the intervention variable and the SPEI.

The data requirements for using the model for impact evaluation are stricter than those necessary to simply calculate the model. If the microeconomic dataset used for the analysis is not the product of a randomized control trial, it must be, at minimum, a two-period panel dataset such that household fixed effects can be used to control for unobserved heterogeneity between beneficiary and non-beneficiary households which could bias the results. While a two-period panel can be used to evaluate the climate dimension and to get a rough sense of the general direction of consumption paths, impact assessments concerned predominantly with consumption dynamics should use at least three periods of panel data. Indeed, more frequent panels allow for the inclusion of lagged consumption data, for instance allowing for a more flexible estimation of recovery trajectories. At this time, we can cannot conduct an impact evaluation for resilience with the DLNM model, as further research is needed in order to extend the DLNM model to the use of fixed effect regressions. However, the data requirements and regression specification would be similar to that of the OLS model that we present here.

As an example of the application of our model to impact evaluation, we estimate the effects of various climate adaptation strategies on household weather sensitivity. This example is motivated by the fact that the frequency of extreme weather events is predicted to increase with climate change [49]. A key question is whether households are taking actions to adapt to these long-term changes in temperature and rainfall

[11] As we selected a decay function, the resulting confidence intervals are very narrow. We therefore replace the confidence intervals calculated by the model with an arbitrary confidence interval equal to plus or minus one year of recovery. The confidence intervals listed are therefore not precise but are rather only indicative of the existence of uncertainty regarding the recovery time. Further research is needed in order to investigate whether bootstrapping techniques are appropriate for calculating confidence intervals with a DLNM model estimated with a decay function.

and, if so, whether these actions have any impact on household vulnerability and resilience. The question we seek to address is thus: does the climate-consumption curve change because of adaptation?

We conducted our example impact evaluation based on data from the ENBCCA survey, as it is a panel dataset and includes variables related to climate change adaptation strategies for both the 2005 and 2012 surveys. Households were first asked whether they had made any adjustments as a result of changes in rainfall, temperature or climate. If the households responded positively, they were asked to list the types of adaptation strategies they adopted, which can be categorized into four groups: crop adjustments, livestock adjustments, changes in livelihoods and group based adaptation. Table 8 shows summary statistics from the ENBCCA survey data. We see that the most common adaptation strategies in both years were related to crop adjustment. Of particular interest is the evidently large increase in the percentage of households reporting having adopted some type of adaptation strategy between the two rounds.

Table 8: Percentage of households adopting adaptation strategies, ENBCCA dataset

	ADAPTATION	CROP ADJUSTMENT	LIVESTOCK ADJUSTMENT	CHANGE IN LIVELIHOOD	GROUP BASED ADAPTATION
2005	44%	60%	4%	7%	NA
2012	81%	77%	9%	9%	1%

In order to explore the effect of adaptation on resilience, we ran a fixed effects model and interacted the SPEI variable with a dummy variable equal to one if the household demonstrated some form of adaptation and zero otherwise. We conducted our analysis on three different types of adaptation variables. We began by investigating the effect of climate change adaptation in general. We then investigated two specific adaptation strategies: soil conservation and tree planting. For each adaptation variable, we tested two model specifications. In the first, only household fixed effects were included. In the second, household fixed effects, a time dummy and a set of time dummy / adaptation variable interactions were included[12]. Regression results are presented in Table 9.

Due to the use of fixed effects, the results can be interpreted as the estimated effect of adaptation on the change in consumption between rounds. Because the estimated effects show the overall consumption trajectory between years, we refer to the results in terms of “change in consumption between periods” rather than in terms of “resilience”.

We first interpret the results from the model with the general adaptation variable. Model (1) shows the estimated effect at the sample average (without the time dummy, nor considering differences between trajectories of early and late adopters). Under normal weather conditions, when the SPEI equals zero, adaptation does not increase expected food consumption, as the coefficient on the adaptation variable is not significant. Rather, the main terms of interest are the SPEI and the SPEI / adaptation variable interaction term which summarize weather sensitivity.

In order to summarize the impact of adaptation, we computed the effect of a drought of a magnitude expected to occur every 10 years on the change in consumption between both rounds. For households that did not adapt between rounds, over the seven year period, such a drought is estimated to have resulted in an average 10 cent decrease in food consumption per capita per day (confidence interval: 4%

[12] The causal relationship between weather resilience and adaptation strategies can run both ways. More resilient households might be in a better position to adopt an adaptation strategy while, conversely, adaptation can increases resilience. Therefore, finding a positive correlation between resilience and adaptation is not sufficient to prove that adaptation causes an increase in resilience. The inclusion of a year dummy and interactions between the year dummy and the adaptation variable allow the consumption trajectories of several household types to vary: those that never adapted, those adapted only in the first round, those that adapted in both the first and second rounds, and those that adapted only in the last round. Furthermore, the use of household fixed effects reduces the risk of obtaining biased results caused by unobservable characteristics correlated with the decision to adapt, such as differences between households’ overall farm management capacities.

to 20%)[13]. Comparatively, for households that did adapt between rounds, the drought is estimated to have caused only a 5 cent decline in food consumption per capita per day over the seven year period. Adaptation therefore appears to have a positive effect on the trajectory of consumption over time.

Model (2) shows the results when the time dummies are included. On average, there is no difference in weather sensitivity between both rounds, as shown by the fact that the SPEI squared / time dummy interaction term is not significant. However, there is a large difference between households that had adapted from 2005 onward and those that never adapted.

The households that adapted in 2005 are the most weather sensitive group but the least weather sensitive group in 2012. A drought in 2005 causes them to experience a decline in food consumption of 13 cents per capita per day (CI: 7 cents to 22 cents) over the subsequent five years. Conversely, as of 2012, a drought of similar magnitude is not expected have a statistically significant effect on their consumption trajectory. By contrast, those who never adapted saw their weather sensitivity increase over time.

[13] $-0.0626 * -1.28^2/0.53 \approx 20\%$

Table 9: Impact of adaptation, soil conservation and tree planting on change in consumption between 2005 and 2012, ENBCCA

CHANGE IN FOOD CONSUMPTION BETWEEN 2005 AND 2012	ADAPTATION		SOIL CONSERVATION		TREE PLANTING	
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	-0.0582	0.248***	0.160***	0.2653***	-0.0302	0.1983**
	(0.0355)	(0.0572)	(0.0339)	(0.0541)	(0.0346)	(0. 0587)
$SPEI^2$	-0.0626***	-0.0832***	-0.0259*	-0.0862***	-0.0363***	-0.0877***
	(0.0220)	(0.0229)	(0.0137)	(0.0174)	(0.0123)	(0.0162)
Variable *$SPEI^2$	0.0473*	-0.0560*	0.0179	-0.0289	0.0232	-0.0573**
	(0.0255)	(0.0286)	(0.0201)	(0.0240)	(0.0204)	(0.0269)
Variable *2012		-0.241***		-0.231***		-0.225***
		(0.0924)		(0.0750)		(0.0778)
$SPEI^2$*2012		-0.0858		0.0195		-0.115*
		(0.0817)		(0.0567)		(0.0660)
Variable *$SPEI^2$*2012		0.228**		0.126		0.311***
		(0.0946)		(0.0912)		(0.0905)
2012		-0.173**		-0.1142**		-.1953***
		(0.747)		(0.680)		(0. 0435)
Constant	0.658***	0.697***	0.543***	0.676***	0.631***	0.745***
	(0.0265)	(0.0298)	(0.0180)	(0.0306)	(0.0153)	(0.0252)
Observations	1864	1864	1888	1888	1888	1888
R^2	0.009	0.148	0.045	0.158	0.006	0.143

Standard errors in parentheses (robust to error clusterization at the Woreda level)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We now turn to the results of the estimation for the two specific adaptation strategies: soil preservation and tree planting. We are interested in soil preservation because the UN declared 2015 as the international year of the soil, with the aim of raising awareness about the role soil preservation can play in food security. Indeed, soil erosion has been shown to decrease crop productivity and to increase the detrimental effects of drought and floods.

The results of the impact evaluation of soil conservation on consumption shows that on average, there is a large and positive effect of soil conservation techniques on the expected change in food consumption between rounds, meaning that soil conservation positively affected households' consumption trajectories between 2005 and 2012. This is demonstrated by the significant coefficient on the soil conservation variable. However, we do not find any effect of soil conservation on weather sensitivity at the sample average, as the soil conservation / SPEI squared interaction term in Model (3) is insignificant. Neither do we find an effect when accounting for the point in time at which the strategy was adopted, as shown by the insignificance of the interaction term between the year dummy, the SPEI squared and the adaptation variable in Model (4). It therefore seems that although soil conservation does have a positive effect on well-being over time, it is primarily a result of productivity enhancement (decreasing poverty) rather than due to a decrease in weather sensitivity.

The second climate change adaptation strategy that we explored is tree planting. Ms. Wangari Maathai, the founder of the Green Belt Movement and Nobel Peace Prize winner, argued that planting trees can result in both important positive agro-environmental and socio-economic impacts. She suggested that trees help to bind the soil, preventing erosion; store rainwater, increasing the net balance of water in the ecosystem; provide firewood; and ultimately promote food security.

Tree planting is not an adaptation strategy that produces immediate results, as it takes time for trees to grow. Therefore, the inclusion of the time dummy is useful for understanding the dynamics of its effect. Indeed, results show no effect of tree planting at the average, when time is not taken into account, as shown in Model (5). However, Model (6), which includes the time dummies, shows that tree planting has a large effect on weather sensitivity. This is demonstrated by comparing the anticipated impacts had a 10 years' return drought occurred in 2005 versus in 2012. For those who did not plant trees, a drought in 2005 would be expected to cause a 13 cent (CI: 10 cents to 37 cents) decline in food consumption per capita per day over the subsequent five years. The same drought in 2012 would be expected to cause a 31 cent (CI: 12 cents to 50 cents) decline. Importantly, for the early adopters, the picture is reversed. A drought in 2005 would be expected to cause consumption to fall by 22 cents over the subsequent five years, while if the same drought were to occur in 2012, it would have no significant effect. Comparing the tree planting and soil conservation adaptation strategies suggests that tree planting may be a more effective strategy for decreasing weather sensitivity.

We present these results in order to illustrate how the standard OLS model could potentially be used for impact evaluation, as well as the limitations involved. A two-year panel dataset allows us to paint a limited, but still useful picture of behavioral change or other interventions on consumption dynamics. Because there are only two years' worth of observations for each household in the ENBCCA dataset, we can only draw a straight line between consumption in period 1 versus consumption in period 2. An interesting extension would be to use a three year panel dataset. The model could include additional lagged consumption values as well as their squares and cubes in order to allow for a more flexible model of the consumption trajectory, as done in the dynamic asset poverty trap literature [14, 50]. In any case, we note that estimating a nonlinear consumption trajectory for impact evaluation would require a higher frequency household panel dataset with at least three rounds. This is a precondition for using a standard econometric model to estimate the proposed weather resilience index above in a monitoring and evaluation framework.

Further work is also needed before we can apply the DLNM methodology for impact evaluation. The first paper using an interaction variable with the DLNM model was only just published in 2015 [51]. Furthermore, it is not yet clear how household fixed effects could be included in the DLNM model.

6.3 EARLY WARNING

The DLNM model can be used for early warning in two ways. First, after estimating the cumulative effect of weather on consumption, we can forecast weather vulnerability and weather resilience scores by plugging in observed weather conditions. Second, we can produce vulnerability and resilience maps by allowing the relationship between weather and consumption to vary spatially. To do this, we run local regressions on the DLNM model and smooth the resulting parameters over the map to create vulnerability and resilience surfaces.

6.3.1 FOOD INSECURITY FORECASTING WITH THE DLNM MODEL

Although a household might be able to cope with a single drought, two droughts in a row might exceed its absorptive capacity. One of the interesting applications of the DLNM model is that it can estimate the cumulative effect of successive weather shocks. By accounting for the history of each household's weather shock exposure, we can assess whether it is at its optimal level of consumption when a shock occurs or whether it is still recovering from a previous weather shock. This type of analysis could be used to improve food security forecasting.

For this analysis, we employed the 2012 LSMS dataset (collected between January and March) because of its wide geographical coverage. We relied on the preceding 15 years of SPEI base data (1996-2011) to allow for a total of 15 years of lags. Based on these datasets, we aimed to predict consumption from 2013 to 2016.

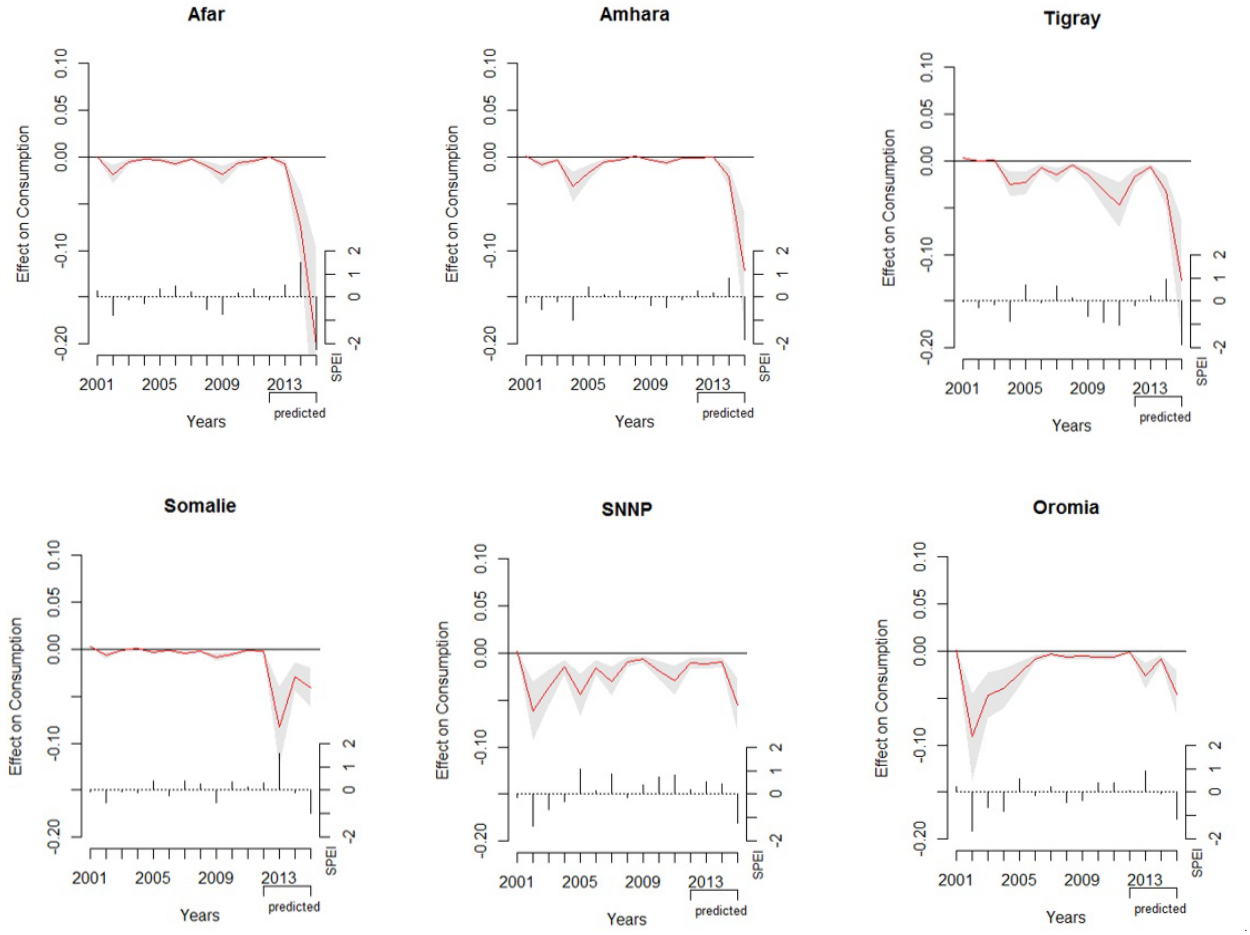
The first step was to estimate the relationship between the weather that occurred over the 1996 to 2011 period on 2012 consumption levels. This gave us two types of information: how much weather variation in a given year affects consumption (the exposure relationship) and how fast this effect fades over time (the lag structure of the effect). We conducted this analysis in Section 6.1.3. For the graphical representation, we refer to Plot C in Figure 7 above.

The next step was to use this relationship in combination with additional weather data for 2012 to 2015[14] to compute the predicted cumulative effect of weather on consumption over the period 2000 to 2015. The idea is that the effect of each weather event fades gradually over time according to the lag structure of the model. The cumulative effect adds the effect of each new weather shock to the lingering effects of the previous shocks. Once the cumulative effect was estimated, we were able to use the weather conditions in 2015 to predict consumption over the January to March 2016 period.

Figure 10 shows the resulting 2016 forecasts for the six regions of Ethiopia for which the LSMS contains data. The vertical axis shows the cumulative effect of past weather events on consumption. A value of zero represents the status quo, which is not adversely affected by weather. Average weather conditions in each region were used to compute the dynamic cumulative effect of weather. At the bottom of each graph, we added the SPEI value for the corresponding year. Note that for the SPEI data, the horizontal axis corresponds directly with the year of the shock. However, the date on the horizontal axis provides the date at which the forecast is produced for the January to March period of the following year. For instance, the SPEI value in 2015 reflects 2015 weather conditions. However, the corresponding effect on consumption value represents how the cumulative effect of weather up to 2015 is forecasted to affect expected consumption in 2016.

[14] Note that the SPEI index used for the 2012 to 2015 is not the same as the one used for the analysis. Indeed, the SPEI base dataset is not constantly updated and therefore the 2015 data were not available. In order to preserve some consistency in the post-2012 forecast, we used the SPEI index available from the global drought monitor (http://sac.csic.es/spei/map/maps.html), accessed on September 30th 2015. This version of the SPEI is based on the Global Precipitation Climatology Centre (GPCC) precipitation dataset and the PET is computed with the Thornthwaite equation using temperature NOAA NCEP CPC GHCN_CAMS gridded dataset. Values above and below -2.33 and 2.33 were censored.

Figure 10: Food security forecasts up to early 2016, LSMS dataset



Afar, Amhara and Tigray are all predicted to be severly affected by the current drought in 2016. In fact, the model predicts that this drought will have the most drastic consequences of any weather shock in the past 10 years, causing consumption to fall from normal by up to 20 cents per capita day in the Afar region and 10 cents per capita day in the Amhara and Tigray region. Conversely, while the shock will be felt in Somali, SNNP and Oromia, the resulting fall in consumption is not likely to be as bad.

The results of the forecasts compare well with the October to December 2015 FEWS NET forecast[15], which categorizes large parts of Afar, Amhara and Tigray as stressed or in crisis. Results also correlate well with an East Africa flood update from OCHA, which signaled displacement in the Somali region caused by flooding in 2013[16].

From a methodological point of view, these graphs highlight the importance of considering historical weather events when assessing the effect of a given weather shock. A mild drought could have a negligible effect if it happens after a series of good harvests. However, a series of mild droughts might have a very negative effect, as demonstrated by the effect of the 2009-2010 series of mild droughts in Tigray. The current situation in Afar also highlights this issue well. The effect of the current drought on expected consumption in 2016 is particularly drastic because households were exposed to excessive rainfall and

[15] FEWS NET website http://www.fews.net/east-africa, last consulted on the 10.10.2015. Shapefiles for FEWS NET food security forecasts are available for download directly from the website.

[16] Eastern Africa: Flood updates (as of 17 May 2013), http://reliefweb.int/report/kenya/eastern-africa-floods-update-17-may-2013, accessed on the 25 of September 2015.

flooding in 2014[17], from which they were not able to recover before the drought hit. This analysis demonstrates the importance of considering historical weather events in order to assess at which point of the recovery path households are located when the shock occurs.

Again, these graphs only serve as an illustration of the potential use of the DLNM model. Particular caution is required in interpreting results from the Afar and Somali regions, as the LSMS is not statistically representative for these areas. The method demonstrates how the DLNM model can be applied for predictive purposes and can potentially identify food security problems arising from cumulative small shocks rather than just focusing on the immediate impact of major shocks, which tend to be the focus of early warning and needs assessments. Clearly, with more recent and disaggregated LSMS data, forecasting accuracy could be improved.

6.3.2 VULNERABILITY AND RESILIENCE MAPS

The DLNM model can also be used to identify vulnerability hotspots and to draw resilience maps, which could prove useful both for policy targeting and in an early warning context. The only change we make to the model in order to produce the maps is that we allow the relationship between weather and consumption to vary spatially. Once local parameters are obtained, we can smooth them over the map in order to create vulnerability and resilience surfaces. Furthermore, current weather conditions could be plugged into the model (as in the preceding section) in order to predict likely food insecurity levels across the country for the next season.

To illustrate vulnerability and resilience mapping, we used the LSMS dataset because of its large spatial coverage. We began by testing for the presence of spatial autocorrelation in the residuals of the OLS regressions with a Moran I test (results in Table 10). When applying a simple model with no explicative variables other than the SPEI, we rejected the null hypothesis of no spatial autocorrelation at a high confidence level. However, once regional and agro-ecological zone controls were added, we failed to reject the null hypothesis. This suggests that although weather sensitivity might vary throughout the country, the variation appears to be inter-regional, such that weather sensitivity does not vary within each agro-ecological zone of each region. The inclusion of regional and agro-ecological dummies is successful at controlling for spatial heterogeneity, which could have biased the results of the OLS regressions presented in the preceding sections.

Table 10: Moran I statistic

		NO CONTROLS	WITH CONTROLS
Sample estimates	Observed Moran's I Expectation Variance	3.265334e-02 -4.505390e-04 9.695265e-07	-7.503707e-03 -1.202956e-03 4.878897e-07
Standard Deviate p-value		33.620 <2.2e-16	-9.021 1

In order to investigate how vulnerability and resilience vary across Ethiopia, we estimated the DLNM model locally. To do so, we followed a similar procedure as Gasparrini et. all used in their recent multi-country analysis of the variability in the dynamic association between heat-waves and mortality [51]. In each country, time series of temperature and mortality data were available for several cities. The authors [51] began by fitting a DLNM model on each time series and then then pooled the estimates by country via multivariate meta-analysis.

[17] OCHA signaled localized heavy rains in September and October 2014 which 'produced flooding in Afar, SNNP and Somali regions, triggering displacements, and loss of lives and livelihoods'. Ethiopia Weekly humanitarian bulletin, 20 October 2014. http://reliefweb.int/sites/reliefweb.int/files/resources/Humanitarian%20Bulletin_20%20October%202014.pdf, accessed on October 1st, 2015.

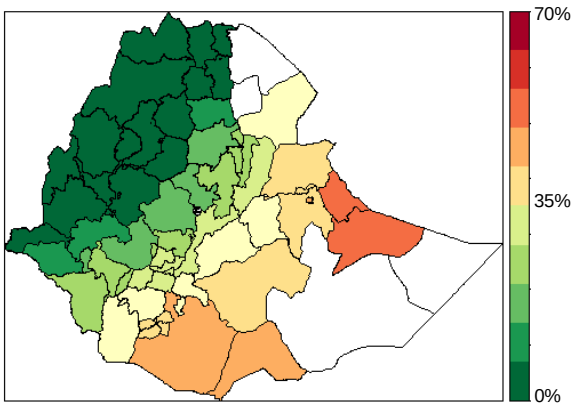
In our analysis, we began by identifying, for each of the 3,700 household in the dataset, all of the "neighboring" households within a maximum distance of 200 km. Remote households with less than 100 neighbors were assigned the 100 closest households as neighbors. We then constructed a restricted sample for each household, which contained the data on both the household itself and its neighbors. As a result, we had as many subsamples as the number of households. These subsamples play the same role as the city time series in the Gasaparrini et. al approach.

In our second step, for each subsample we fitted a DLNM model. In this process, the optimal lag structure was selected based on the AIC criteria, assuming a decay function of 15 years for the time dimension and a quadratic function centered at zero for the SPEI dimension. From these models, we obtained a series of 3,700 estimates of the relationship between weather and consumption over time. These are the building blocks of the spatial analysis of the weather vulnerability and resilience measures.

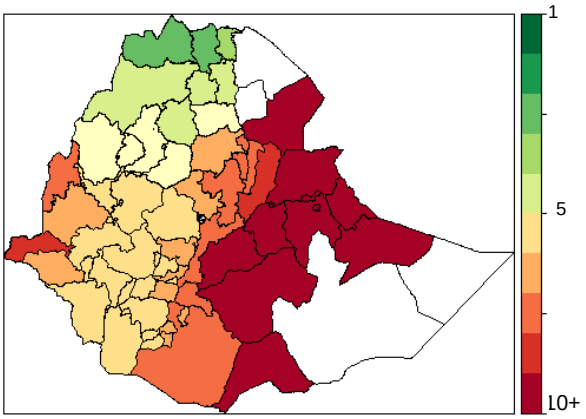
The coefficients derived from each of the 3,700 models were then used as dependent variables in a meta-analysis thanks to the R package mvmeta. We used the geographical coordinates of the household at the center of each sub-sample as the explicative variable. This meta-analysis accounted for the variance of the coefficients estimated in the first stage and was used to predict the weather sensitivity curvature and the recovery slope according to the relationship between weather and consumption over time estimated locally. Finally, in order to construct the map, we took the zonal average of the local vulnerability and resilience indices. Map 1 shows the results.

Map 1: Vulnerability and resilience maps, LSMS with the DLNM model

A. Drop in consumption resulting from a 10 years return shock (% of the poverty lines)



B. Number of years to recover from a 10 years return drought



Map A presents the average drop in consumption caused by a drought of a magnitude expected to occur every 10 years, expressed as a percentage of the poverty line. Zones in red are expected to face a sharp drop in consumption, while the consumption of households in green will be marginally affected. Zones in white represent those for which the LSMS does not provide sufficient data.

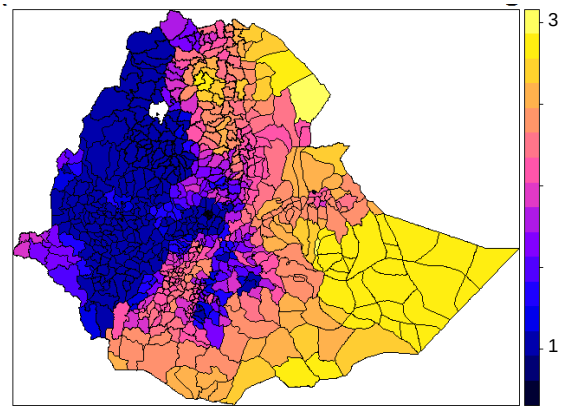
Map B shows the recovery times following such a drought. In terms of the resilience index as we have defined it, households taking more than five years to recover are not resilient. Thus, on average, zones in green are resilient while zones in orange and red are not resilient. Most parts of the country will take more than 5 years to recover. In fact, these areas are very likely to be hit by a subsequent weather shock while still recovering from the one that we modeled.

Looking at the various regions, we see that the lowlands are both highly vulnerable and not resilient with respect to a 10 years' return drought. As we would expect, some zones are both more vulnerable and more

resilient than others. Interestingly, other areas share the same vulnerability profile but exhibit different speeds of recovery. We will investigate this further below.

For the sake of comparison, Map 2 shows the average acute food insecurity forecast from the USAID FEWS NET project over the period 2008 to 2015[18]. Our maps coincide with the FEWS NET forecasts relatively well, which suggests that the DLNM model provides sensible results. Again, the DLNM model has been fitted with only one year of the LSMS data and 15 years of weather history.

Map 2: 2008-2015 Average FEWS NET acute food insecurity forecast



Further work is needed before the DLNM framework can be used as an information tool. First, the problem of spatial autocorrelation must be taken into account. Although it is on the DLNM community's research agenda, at the moment, there are no available statistical techniques for doing so. In addition, the LSMS is representative only at the regional level and only for Tigray, Oromia, Amhara and the SNNP. Other datasets could be used in order to provide representative results at a lower administrative unit level. For instance, the 2010/11 Ethiopia Household Income and Consumption Expenditure (HICE) dataset is representative at the zonal level.

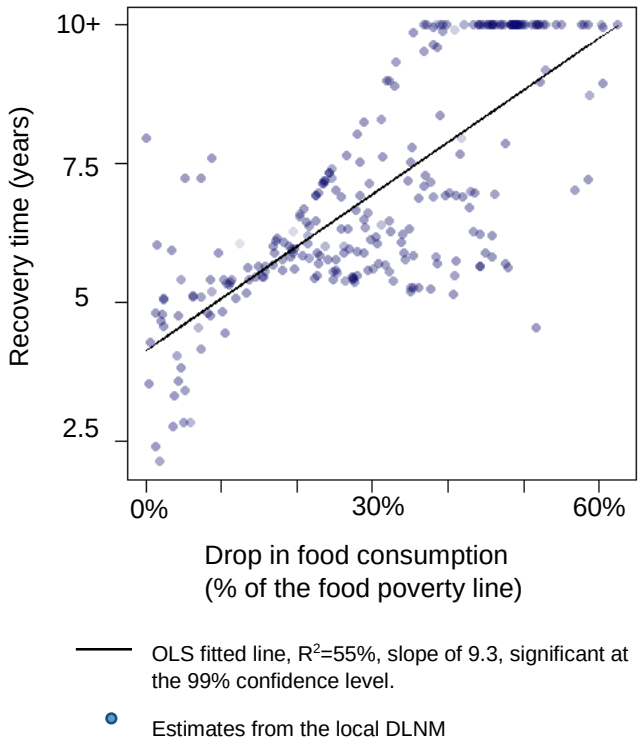
6.4 TEST OF INDEPENDENCE BETWEEN RESILIENCE AND VULNERABILITY

Map 1 suggests that the two dimensions of well-being are correlated over space, as the most vulnerable zones tend to be the least resilient. However, there are a few exceptions. In order to determine if vulnerability and resilience are empirically distinct, we tested whether the food consumption gap (change in food consumption between normal and adverse conditions) and recovery duration vary together or whether there exist some households that exhibit the same food consumption gap but different speeds of recovery, or vice-versa.

In order to compare the food consumption gap and the speed of recovery after a given shock, we used the 3,700 predicted coefficients obtained via the meta-analysis of the local DLNM results used in the Map 1. Figure 11 shows the scatterplot of the results. As expected, the recovery time depends strongly on the initial drop in consumption. For every 10% decline in consumption, the average recovery time increases by approximately one year (0.93), as shown by the OLS fitted line. These results are significant at the 99% confidence level, and 55% of the variation in recovery time is explained by the initial drop in consumption.

[18] A simple average is taken over the period despite the change in the scale FEWS NET to the IPC scale over the period.

Figure 11: Correlation between vulnerability and resilience



Nevertheless, there is some heterogeneity in recovery time. While some households exhibit large food consumption gaps, they nevertheless take several years to recover from the shock. These households fall to the upper left of the fitted line. Conversely, other households may experience large drops in consumption but still recover relatively quickly, as represented by the observations that fall to the lower right of the fitted line. Resilience is clearly not independent from vulnerability; however, neither is it the inverse of vulnerability.

Further development of the DLNM framework could provide a clearer answer to the question of independence. For instance, the model was fitted with similar functional forms for each local regression. There is therefore a high probability that some of these results are driven by our parametric assumptions, i.e. a quadratic function reaching a peak in normal weather conditions and a lag structure following a decay function. More advanced data mining could help address these issues, as would better integration of the spatial structure of the data in the estimation.

7 POLICY IMPLICATIONS

Policy implications of this methodology can be classified in two groups: policy development and early warning.

7.1 POLICY DEVELOPMENT

The differentiation between the dimensions of well-being, represented by separate measures for poverty, vulnerability and resilience, allows for policymakers and planners to subsequently develop a more differentiated response to the specific profile of population groups of interest.

Following the framework that we present, policies aimed at reducing weather vulnerabilities are essentially *ex ante* risk mitigating strategies. Their goal is to make households less sensitive to weather shocks. They

include, for instance, improved livelihood diversification, improved access to off-farm job opportunities, access to irrigation and drought tolerant crops, soil restoration activities, and afforestation schemes that improve the capacity of the ecosystem to store water. All of these interventions share the common goal of reducing the effect of weather shocks on household well-being by reducing the household's exposure to weather variations.

By contrast, resilience policies can be defined as strengthening *ex post* risk coping strategies, i.e. increasing the ability of households to recover from shocks more quickly. These might include weather index based insurances, improved access to financial services such as savings, and improved access to mobile money in order to ease cash transfers between different parts of a country and remittances from abroad. These types of policies share the common goal of accelerating post-shock recovery. We provide a classification of policies in Box 6.

Box 6: Classification of policies

Chronic poverty reduction policies for long-term equitable growth:

- Economic growth (e.g. through macro policies and investment)
- Redistribution (e.g. through regular cash transfers, land reform)
- Market policies
- Improved public services (e.g. education and healthcare)

Vulnerability reduction policies to avoid the full brunt of the shock:

- Risk reduction (e.g. drainage, irrigation, livelihood diversification)
- Early warning systems
- Emergency stocks

Resilience building policies for hastened recovery:

- Public and private insurance
- Post-crisis recovery investments
- Adaptive capacity / ex-post risk coping capacities (e.g. direct delivery of cash, food or non-food and DRM)
- Graduation systems to ensure recovery when the ex-post intervention ends

Transformative policies address the entirety of the well-being framework, impacting on chronic poverty reduction, vulnerability reduction and resilience building at once. They address underlying drivers of risk and vulnerability and promote social cohesion through public assets and human capital. For example, scalable social protection schemes (e.g. the Productive Safety Net Program in Ethiopia) address chronic poverty through regular cash and in-kind transfers, vulnerability through early warning predictions that trigger scale-ups, and resilience through the scalability component that expands services through routine mechanisms in the event of a shock. Furthermore, public works programs for the poor (also a component of the PSNP) can address environmental and systematic vulnerability (i.e. through terracing) while speeding up recovery (i.e. by building roads, thus connecting farmers and markets).

In addition, the methodology that we propose could help identify high priority regions within and across countries, as the indices are comparable across settings. We could estimate the number of vulnerable and non-resilient households as well as their locations. Depending on the vulnerability and resilience scores of each region, policy makers could better assess which interventions should be supported where.

The climate vulnerability index could also be used as a budgeting tool. A policy aiming at reducing climate vulnerability should not cost more, per year and beneficiary, than the average increase in poverty caused by weather shocks. If it does, a direct cash or food transfer would be more effective.

Weather sensitivity analysis could help to define thresholds for crisis-modifiers. For instance, we could estimate the minimum size weather shock that would cause a given share of the population to fall into poverty. The corresponding SPEI value could serve as an objective measure for triggering humanitarian funding. The amount of additional funding requirements could also be estimated by computing the weather-induced poverty at least as bad as the threshold-modifier shock. Using the SPEI as threshold-modifier, we would obtain an estimate of the probability that the threshold would be triggered. This could help in linking crisis-modifiers with weather index based insurances.

Vulnerability maps and other early warning tools have been a cornerstone of humanitarian intervention planning since at least the 1980s. The added value of the resilience lens is that it extends planning horizons by estimating recovery paths. Furthermore, by providing an estimate of the time required for the household to recover to its pre-shock level, it can predict the ideal duration of the recovery intervention. The expected average poverty gap over the period could serve as an upper bound for estimating the cost of a post recovery intervention.

7.2 IMPACT EVALUATION

The vulnerability and resilience indices we propose can serve as intermediate outcome level indicators which are comparable across regions and countries. The key question of interest for vulnerability analysis is: does the intervention reduce the fall in consumption following a weather shock? The question for resilience analysis is: does the intervention speed up recovery after a weather shock? As the vulnerability indicators are expressed as a percentage of the poverty line and the resilience indicators are expressed as a percentage of 5-year recovery, they are comparable across regions and countries. The example in this report is the effect of climate adaptation on food consumption.

Under a typical resilience impact evaluation, it is difficult to assess the effect of the intervention on reducing weather vulnerability if no weather shocks are observed during the course of the program. The advantage of the proposed approach is that it relies on a long history of weather events for the dynamic assessment. The variation in recent weather is used to assess whether the program helped to reduce the effect of past weather events on current consumption.

The ideal setting for using the proposed approach is, of course, with data from a randomized controlled trial (RCT), in which the intervention is randomly assigned to a subset of potential beneficiaries. Through the randomized assignment, those who did and did not receive the intervention are comparable and the evaluation yields statistically unbiased results. However, for a variety of reasons, RCT methods are not always feasible or desirable.

In the event that randomized control trials are not feasible, such as when programs apply deliberate targeting using clearly specified criteria, a range of statistical methods could be used to correct for initial biases. When panel data are available, household fixed effects should be used to control for unobserved heterogeneity.

More research is needed in order to better assess the minimum sample size required to estimate the effect of the intervention on weather vulnerability and resilience. Furthermore, a better understanding of how the modeling strategies respond in the face of non-random allocation of the development intervention would increase the robustness of the results. At the moment, we caution that the single period model would require at least three waves of panel data in order to allow for the estimation of the resilience score. More research needs to be put into the DLNM model before it is ready to be applied for impact evaluation. A further limitation of the framework is that it requires a large geographical spread in order to observe enough weather variation to estimate the model. The methodology is therefore not suited for small-scale programs taking place in only a few closely located communities, for instance. Barrett and Heady have advocated for

the development of a multi-country system of sentinel sites where high frequency measurement would take place [52]. Such datasets would provide the ground work for further development in resilience analysis.

One of the greatest promises of the resilience concept is to bridge the gap between humanitarian and relief interventions. A first step is knowing who is doing what and where. 3W maps are designed to map and track, in real time, which development and humanitarian organizations are implementing what types of activities where. They are based on frequent reporting from partner organizations. Interesting examples include the Kenya Resilience Investment Trackers (http://kenya.droughtresilience.info/) and the OCHA Sahel Online Reporting System (http://ors.ocharowca.info/Default.aspx). IGAD is setting up a similar system for its member countries

The 3W maps could be overlaid with poverty, vulnerability and resilience maps in order to assess, in near-real time, which resources have been put where given the current and anticipated needs. An information tool based around the concept of 3W maps could foster coordination between development and humanitarian actors, avoid duplication of efforts and improve policy targeting.

8 NEXT STEPS

Research on resilience estimation and definition is still in an early stage. While promising, the work described above has had a fairly broad focus across a range of issues, each of which require further refinement. There remain a number of important questions to be considered in the future and methodological issues that must still be overcome to fully realize the promise of the model. The following offers a partial list of next steps in the development of this methodology.

- One of the key benefits of the proposed methodology is that it allows for cross-country comparison in terms of the magnitude of the vulnerability and resilience indices, for comparison of impact evaluations across programs and locations, and for a more objective basis to compare needs in an early warning context. Testing the model in other countries should therefore be an essential component of further development, as it would, for instance, allow us to test stability of the results across countries, better understand whether our initial results are driven by unobserved local economic dynamics, and offer more variation in weather conditions and consumption patterns.

- Further development of the DLNM model is critical in order to be able to provide a more complete set of estimates of our vulnerability and resilience measures across locations. The development of a spatially varying DLNM model is a high priority on the DLNM research community's agenda, which we will follow and support where possible. To obtain estimates across welfare groups, which was not directly addressed in this report, it should be fairly straightforward to employ spatially varying quantile coefficient models.

- Additional work on the specification of the climate risk indicator itself is also required in order to ensure that it captures crisis conditions in the most complete and comprehensive fashion possible. In particular, further collaboration with agroclimatologists at NOAA will be necessary to realize the full potential of the SPEI-NOAA data for resilience analysis. While the model results using the SPEI NOAA variable were not as stable as with the SPEI base measure, the SPEI NOAA indicator is based a new and higher resolution evapotranspiration dataset produced by NOAA and the CHIRPS precipitation dataset and, therefore, warrants further exploration as a measure of climate risk.

- In order to apply the methodology to impact evaluation, it will be necessary to take into account co-founding factors in the DLNM model either via the inclusion of fixed effects or by propensity score matching. The work on interaction variables with DLNM models is progressing quickly among the DLNM research community, with a first article published in 2015 [51]. Access to data from a program evaluation, with a clear Theory of Change and actual program exposure data, rather than the surveys utilized in this study that were designed for other purposes, would also assist in further refinements of the model for use in this context.

- A more systematic testing of the forecasting ability of the model is also needed to ensure its effective use in early warning. Improvements in the model and the specification of the climate risk variable described above will significantly improve forecasting power. Using another dataset from Ethiopia with a larger sample and better geographical representativeness would also strengthen the coverage and accuracy of the forecasts. Finally, in order to provide long-terms forecasts, it will be necessary to develop better methods to account for uncertainty over the forecasting horizon as well.

- Finally, as climate risk is not the only factor that can lead to crises in developing countries, it will be important to integrate other risk factors, particularly market risk and conflict, into the model. Although the impact of SPEI on conflict risk has been extensively investigated and tested [53, 54], integrating conflict risk into the model presents considerable data management and methodological challenges. For the analysis of market price risk, it would be necessary to link geo-referenced food crop prices that are available to FEWS NET across a large number of countries to geo-referenced household data following a similar approach as that with climate dynamics. Once we define an appropriate price risk indicator based on those price data sets, it should be possible to understand the relationship between price dynamics, weather conditions, and household well-being over time.

9 CONCLUSION

Research on resilience estimation and definition is still in an early stage. Our aim with this report is to contribute a new and different perspective to the field. Our research demonstrates not only that resilience is a valid policy concern related to, but still distinct from, the concept of vulnerability, but that resilience measurement is feasible using existing data sets broadly available throughout most developing country contexts. However, again, there remain a number of methodological issues that must still be overcome to fulfill the promise of these preliminary results and, ultimately, to provide a set of resilience measurement tools that meet the full range of decision-making needs for resilience policy and program development and evaluation.

By proposing a *narrow* definition of resilience, we distinguish the concept from the already existing and policy-relevant concepts of chronic poverty and vulnerability. While poverty analysis reflects a static view of well-being in relation to a cut-off point that defines a state of well-being, vulnerability analysis is concerned with the drop in well-being following a shock. In contrast, the narrow view of resilience is concerned with the speed of recovery in well-being after a shock. We provide a set of indices and techniques for measuring vulnerability and resilience to short-term weather shocks and to the expected long-term variations in climate patterns in general. Because the analysis is based on universally available measures of climate risk and standard, objective indicators of well-being, the vulnerability and resilience indices we define are comparable across population groups and countries, as well as over time.

The results presented above suggest that the model has the potential to inform decision-making across the full range of the resilience programming cycle, including policy and program design (in estimating the magnitude of the problem across population groups and locations), monitoring progress toward higher order resilience objectives over time (by assessing changes in the degree of vulnerability and resilience over time), and assessing the impact of policies and interventions on targeted populations (by attributing the change in vulnerability and resilience to specific interventions). While the model here is tested for the case of climate risk and implications for food consumption, it is applicable to other measures of well-being, such as nutritional status, for example, and other sources of risk, like market price risk. Therefore, it is suitable for application across a fairly broad range of sectors of investment. This fact, combined with the narrow definition of resilience that forms the basis of the model, ensures that the vulnerability and resilience indicators can be directly mapped to the Theory of Change to serve as effective impact measures across a range of possible interventions.

Given that we do find suggestive evidence that vulnerability and resilience differ empirically, there are two main advantages of distinguishing resilience, as the recovery path, from vulnerability. Optimal policies to address poverty, vulnerability and resilience might differ. For instance, vulnerability-focused interventions might aim to decrease households' exposure to weather shocks by fostering livelihood diversification or irrigation. Conversely, resilience-focused interventions might aim to speed up post-shock recovery by setting up scalable social safety nets or insurance programs, or by increasing access to saving and other financial services. Identifying the vulnerability and resilience profiles of households or regions can help organizations tailor an array of policies and programs to the specific needs of potential beneficiaries.

The measures of vulnerability and resilience also have significant implications for humanitarian programming. As demonstrated above, it is possible to develop real-time estimates of the degree of the magnitude of consumption losses across locations as a result of a weather shock, estimates that can take into account the impact of previous shocks as well. In addition, although not directly tested in this paper, it should also be possible to predict the recovery path of populations in locations affected by a weather shock. Therefore, these tools could support humanitarian needs estimates, not only in the short-term, but over a protracted humanitarian response. Understanding the recovery path of affected populations may also help guide decisions on when and where to graduate populations from humanitarian relief to other forms of assistance. The fact that these measures are comparable across countries suggests that their application could support humanitarian resource allocation decisions on a far more objective basis than is currently the case.

Again, while the results presented here are by no means complete, they are suggestive of the potential benefits of the approach. Additional work is necessary to refine the specification of the model to suit the complete set of requirements for vulnerability and resilience measurement. Additional work on the specification of the climate risk indicator itself is also required to ensure it captures crisis conditions in the most complete and comprehensive fashion possible. As part of a future research agenda, it will also be necessary to refine the application of the model to the evaluation context, to ensure its predictive power and ability to adequately attribute the impact of resilience investments on greater stability in household well-being in response to climate shocks. Finally, because climate risk is not the only factor that can lead to crises in developing countries, it will be important to test the model against other risk factors, particularly market risk.

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APPENDICES

APPENDIX A: CALCULATION OF CONSUMPTION VARIABLES

The ENBCCA asks households how much they spent on four different food groups in the last month. We sum these values to calculate monthly food expenditure. It also asks how much of their own production from each season (*meher*, *belg* and perennial) they consumed for 69 different crops and how much of their own livestock production they consumed for 15 types of livestock. We sum these values and divide by 12 to calculate monthly own production quantity. Finally, the survey asks about the quantity of food aid households received over the past year. Again, we sum these values and divide by 12 to calculate monthly quantity of in-kind food aid. We calculate the value of real consumption from own production and food aid by normalizing the values by the Paasche index where the local price is computed according to the median farm gate price. Finally, we sum the values of food expenditure, own production and food aid to compute the total consumption variable and divide by 30 to calculate the value of consumption per day.

The World Bank (WB) Development Research Group provided the food consumption variable for the LSMS. The WB variable was constructed using a conservative and careful approach that involved winsorizing the data, or replacing the high and low values with upper and lower bound thresholds. The nominal values were then divided by the price index computed by the Central Statistical Agency of Ethiopia in order to obtain the food consumption variable. Prior receiving the food consumption variable end of August 2015, we used a food consumption variable computed in the same manner than the ENBCCA and the WB food consumption variable, although we performed more ad-hoc cleaning on the raw food item data. We choose to use only the WB variable because it will become the standard food variable for researchers using the LSMS.

For the ERHS, we used the food consumption variable corrected by the price index provided in the dataset.

In terms of poverty line, we used the data provided in the ERHS. The poverty line is set according to the cost-of-basic-needs (2400 kcal plus essential items), at 50 birr in 1994 values [55]. We reduce the poverty line by a further 17% in order to get the food poverty line, i.e. the share of expenditure going to non-food items among the poorer half of the sampled households in 1994[56]. The resulting poverty line is 41.5 birr in 1994 values, or 0.43 2014 USD per person. Compared to the much higher 1.25 USD international poverty line, the cost of basic need approach focuses on the poorest groups, who are most likely to benefit from a humanitarian intervention and who are most in need of development policies.

APPENDIX B: VULNERABILITY AND RESILIENCE INDEXES

VULNERABILITY INDICES

Following a number of authors [32-38], our weather vulnerability index is based on the Foster-Greer-Thorbecke (FGT) class of poverty measures [39]. As we are interested in expected poverty caused by a weather shock, we take the difference between expected FGT in normal and expected FGT in adverse weather conditions, for example a drought with a magnitude expected to occur every 10 years. Weather vulnerability is thus defined as the expected weather-induced poverty gap.

The individual-level *weather vulnerability index* is expressed as:

$$V_{W,i}^{\alpha}(s) = \Delta_s {P_i}^{\alpha}$$

where s is the SPEI value of interest (for instance, $s = -1.2$ for a drought expected to occur every 10 years), ${P_i}^{\alpha}$ is the FGT poverty measure of household i, Δ_s denotes the difference between normal and adverse condition s (the 10 year drought), and α increases the weight given to an increase in the poverty of the poorest.

In the this report, we only present results in terms of $\alpha = 1$, i.e. expected poverty caused by a weather shock.

To aggregate these measures at the population level, we simply take the population average:

$$\boldsymbol{V_W^{\alpha}}(s) = \frac{1}{N}\sum_{i=1}^{N} \Delta_s {P_i}^{\alpha}$$

where N is the population size. The meaning is the same, except that now we are talking in terms of population averages. The population-level class of weather vulnerability indices, $\boldsymbol{V_W^{\alpha}}$, can be disaggregated by region or livelihood group.

- With $\alpha = 0$, $\boldsymbol{V_W^0}(\boldsymbol{s})$ is the *weather-induced change in poverty status*. A $\boldsymbol{V_W^0}(\boldsymbol{s})$ score of 10% means that as a result of weather shock s, 10% of the population is expected to become poor next year.
- With $\alpha = 1$, $\boldsymbol{V_W^1}(\boldsymbol{s})$ is the *weather-induced poverty gap* which is expressed as a percentage of the poverty line. A $\boldsymbol{V_W^1}(\boldsymbol{s})$ score of 10% means that as a result of weather shock s, the average population-wide weather-induced poverty gap is expected to increase by 10% of the poverty line in the next year.
- With $\alpha = 2$, $\boldsymbol{V_W^2}(\boldsymbol{s})$ is the *weather-induced poverty severity gap*, which puts greater emphasis on shortfalls that result in higher levels of poverty and can help distinguish between individuals with the same weather-induced poverty gap but who are expected to experience different levels of absolute poverty. If the $\boldsymbol{V_W^0}(\boldsymbol{s})$ and $\boldsymbol{V_W^1}(\boldsymbol{s})$ scores are equal in two regions, interventions should prioritize the region with the highest $\boldsymbol{V_W^2}(\boldsymbol{s})$, where more acute poverty is predicted to take place.

In order to assess vulnerability to weather shocks in general, we define the *climate vulnerability index*. To calculate it, the weather vulnerability scores for each individual, $V_{W,i}^{\alpha}(s)$, are weighted according to the probability of occurrence of each corresponding weather event. It is expressed as:

$$V_{C,i}^{\alpha} = E\left[V_{W,i}^{\alpha}(s)\right]$$

where the expectation, E, is taken over the probability distribution of weather events.

In the this report, we only present results in terms of $\alpha = 1$, i.e. average expected poverty caused by a weather shocks in general.

It can be aggregated at the population level ($\boldsymbol{V_C^{\alpha}}$) or at lower level such as regional or livelihood zone differences.

- With $\alpha = 0$, the first climate vulnerability index, $\boldsymbol{V_C^0}$, is the *climate-induced change in poverty risk*. A score of 10% means that an individual faces a 10% risk of becoming poor because of climate.
- With $\alpha = 1$, the second climate vulnerability index, $\boldsymbol{V_C^1}$, is the *climate-induced poverty gap*; it is the average weather-induced poverty gap. A score of 10% means that an individual is expected to drop 10% below the poverty line because of weather shocks.
- With $\alpha = 2$, the third climate vulnerability index, V_C^2, is the *climate-induced poverty severity gap*, which gives more weight to households whose poverty shortfalls result in acute poverty.

The class of climate vulnerability indices can be used for impact evaluation, as it allows for analysis of an intervention's impact on beneficiaries' climate vulnerability. It can also be used for policy planning, as it can help to better identify climate vulnerability hotspots, improving targeting of future interventions.

Dercon and Calvo [57] propose a set of criteria (axioms) that vulnerability measures should fulfill in order to make sense and be coherent. The first axiom they list is the *poverty focus axiom*: changes in consumption levels above the poverty line should not affect the vulnerability measure. They give the following motivating example. Imagine a farmer facing two scenarios: rain (no poverty), drought (poverty). If her harvest increases in the rainy scenario, she does not become less vulnerable, as the risk of falling into poverty because of the drought has not changed. Therefore, the only scenarios which matter are those in which consumption falls below the poverty line. The poverty focus axiom is one reason why we base our vulnerability measures on the FGT poverty measures. As such, the vulnerability indices proposed herewith satisfy the focus axiom.

The second axiom is the scale invariance axiom. Multiplying all scenarios and the poverty line by the same amount does not change vulnerability score. This axiom allows cross-country comparability using real consumption data. The third axiom is the normalization axiom: vulnerability scores have to be bounded between 0 and 100%. As the weather and climate vulnerability indices are based on the poverty shortfall expressed as percentage of the poverty line, they satisfy both axioms.

The fourth axiom is the risk sensitivity axiom: greater risk increase vulnerability. We can think at it two way. First, SPEI values corresponding to more extreme weather events will implies a lower weather vulnerability. Second, an increase in the frequency of extreme events would change the underlying distribution of the index. If the household doesn't adapt, the results will be a steeper climate consumption curve. Both the weather and climate vulnerability will increase as a results. Similarly, if probability is transferred from a favorable weather conditions to unfavorable condition because of desertification reducing the amount of precipitation for instance, then the climate vulnerability indices will increase (probability transfer axiom).

Lastly, the indices inherit the aggregation properties of the FGT poverty measures. Overall vulnerability is a population share weighted average of subgroup vulnerability levels (additive decomposability axiom) [58]. Overall vulnerability increases if, everything else being equal, vulnerability increase in one subgroup (subgroup consistency axiom) [58].

One of the limitation of using the FGT as building block of the vulnerability index is that it incorporate some assumption about risk preferences. Ligon and Schechter [59] were the first to highlight that the use of FGT hides some assumptions about risk preferences. For instance, the FGT implies increasing absolute risk aversion which is at odd with empirical findings.

Despite these concerns, we choose to design our measures as extensions of the FGT measures. First, FGT are simple, easy to understand and easily communicable, with straightforward interpretations. Second, FGT poverty measure are well integrated in policy design and should be easily actionable. It would be interesting to investigate the use of the constant relative risk measure of vulnerability proposed by Calvo and Dercon [60] as an alternative to FGT. This is however out of the scope of the present report.

RESILIENCE INDICES

As with the class of weather vulnerability indices, the class of weather resilience indices is an extension of the FGT class of poverty measures and is fitted to a specific weather shock. It is based on the insight that more resilient individuals rebound more quickly after a shock. We propose using the speed of recovery after a shock as the building block of the weather resilience indices.

The household is considered resilient if it recover in less than 5 years and non-resilient otherwise[19]. Smaller is the recovery period, more resilient is the household. The index can be expressed as:

$$R_{W,i}(s_1) = 1 - \frac{1}{4}\sum_{2}^{12} I\left(V_{W,i,t}^{1}(s_1) > 0\right)$$

where $V_{W,i,t}^{1}(s_1)$ is the weather induced poverty shortfall at time t given the weather shock at time 1, $I()$ is an indicator function equal to one if the weather induced poverty shortfall at time t is greater than zero. The index sums the number of period where the weather-induced poverty shortfall is greater than 0. The summation is done on period 2 to 12, i.e. from one year after to shock up to ten years after the shock.

A household recovering in 1 year is 100% resilient, a household recovering in two years and a half is 50% resilient and a household recovering in 5 years is 0% resilient. Negative score are given to household needing more than 5 years to recover. A household taking 7 and half years to recover is -50% resilient while a household taking 10 or more years to recover is -100% non-resilient.

The advantage of the index is to be easily communicable. It is comparable across weather shocks as a score of 50%, for instance, means the same whatever the stringency of the shock. It is independent from the vulnerability index as the factor that matters is the time of recovery after a given weather shock whatever the initial drop in consumption is. It can hence be used to compare resilience score between households. It can distinguish between slow and fast recovery. It can be easily aggregated between household. Lastly, we can also distinguish household set on a downward recovery path as a minimum score, i.e. taking more than 5 years to recover, implies a high likelihood of being hit by a second shock when one is still recovering.

The index can easily be aggregated between household groups or at the population average:

$$\boldsymbol{R_W}(s_1) = \frac{1}{N}\sum_{i=1}^{N} R_i(s_1)$$

where N is the population of interest.

In order to summarize a household's recovery paths with respect to the full range of possible weather events, we take the average weather resilience score by weighting weather resilience scores according to the probability of occurrence of each corresponding weather events, i.e. by the SPEI probability distribution. It is expressed as:

$$R_{C,i} = E_s\left(R_i(s)\right)$$

where the expectation is taken over the probability distribution of the SPEI.

The following are a few examples of the interpretation of the results:

- A score of 100% means that the individual is expected to fully recover after one year whatever the shock.
- A score of 50% means that the individual is expected to recover in two years on a half on average.
- A score of 0% means that the individual recover on average in five years.

[19] We choose five years because it is the minimum return period of weather event considered abnormally dry or wet on the Standardized precipitation scale (respectively -0.79 and 0.79 moist), i.e. a return period of 4.7 years).

- A score of -50% means that the individual to recover on average in seven years and a half.

The climate resilience index can also be aggregated between households by taking the population or sub-group average.

The literature has proposed a series of desirable properties of a resilience measurement framework should have (Box 7). The first one is to be multi-scale, allowing for the disaggregation of resilience scores at different levels and at different frequencies [1, 61]. Although we focus in the present report on household level resilience, other unit of analysis could be used such as a community or a region for instance. Furthermore, we can decompose the effect of a given weather shock over time. Lastly, the weather and climate resilience indices we propose satisfy the sub-group consistency axiom, i.e. the resilience score increases if the resilience score of a sub-group increase, and are additively decomposable between groups. The framework can hence be considered as multi-scale.

A second desirable property is to be multi-dimensional, i.e. several types of shocks can be taken into account. At the moment, the indices we propose can take into account drought of flood of various magnitudes. The measure is comparable across weather shocks, i.e. a given score means the same thing for a minor or major drought. Further work would be needed to demonstrate their applicability to other types of shocks such as price spike.

A third desirable property is to be welfare oriented, i.e. bouncing back to the original level should not necessarily be desirable, particularly if the initial condition was a state of poverty. The resilience index only partly full-fill this axiom. Indeed, as we focus on the weather induced poverty, we stop *counting* once the household has reached it pre-shock level of poverty. However, household recovering faster receive a higher score. Hence, shorter is the time of recovery, longer is the time during which household can possibly escape chronic poverty. Therefore, a positive score is the precondition for bouncing back at *higher* level than the pre-shock poverty level.

Fourth, the measurement should be is flexible, allowing to take into account the heterogeneity of response capacities. The resilience index we propose is designed to take into account the heterogeneity in the speed of recovery. Speed of recovery is however only one dimension across which the recovery path can vary. Recover paths might differ in terms of the duration of the spells in acute poverty for instance. We will comment below on making the index more flexible. However, as we sought an index which would be clearly communicable in order to be actionable, we preferred to stick to one dimension, i.e. the speed of recovery.

Fourth, measurement should not fall into a circular argument by choosing the components of resilience *a priori* and then asserting that these components build resilience without testing formally the relationship [61]. As we base our measure on estimated dynamics of consumption over time rather than capacities, we avoid this pitfall.

Fifth, the measurement is risk sensitive: an increase in risk will decrease the resilience score as a household will take longer to recover from a major drought than a minor one. Sixth, it is scale invariant and could be used to compare resilience across livelihood zones or countries. Seventh, it is independent from poverty and vulnerability measure so that we can test if resilience differ from these other dimension of well-being.

The mutual interaction between economic and environmental well-being should be modeled [14]. Further research is needed to adapt the model to such interactions. At the moment, the environment enters only as an exogenous variable via the SPEI index.

Lastly, it is common to apply different weights to outcomes that occur at different points in time in economic analysis of multiple time periods. For instance, when computing the net present value of an investment, profit earned toward the end of the time horizon is given less weight than profit earned at the beginning of the time horizon. However, it is not clear that the same reasoning should apply to intertemporal poverty measurement [62].

For instance, consider two households: household A, which started above the poverty line and ended below it and household B, who started below the poverty line and ended above it. If we were to employ the method of discounting the future, we might suggest that household A is better off than household B, because household A's present high level of consumption would be weighted more heavily while household B's future high consumption would be discounted. However, taking the resilience perspective, we see that household A is attracted to a *lower* basin of attraction (not resilient), while household B is attracted to a *higher* basin of attraction (resilient). Because the resilience lens predominantly concerns the dynamics of consumption over time, we choose not to apply discounting between periods.

Box 7: Desirable axiomatic properties for resilience measurement

RESILIENCE MEASUREMENT AXIOMS	MEANING
Multi-scale	Various units of analysis are possible (individuals, households, communities, regions, etc.) [1, 61], allowing for the disaggregation of resilience scores at different levels and at different frequencies.
Multi-dimensional	Analysis of various types of shocks (droughts, excessive rainfall, price spikes, etc.) is possible.
Welfare-oriented	Bouncing back to the original level should not necessarily be desirable, particularly if the initial condition was a state of poverty.
Not circular	The measure should not fall into a circular argument by choosing the components of resilience *a priori* and then asserting that these components build resilience without testing it is truly the case [61].
Risk sensitivity	An increase in risk should decrease resilience so that household should receive a lower score with respect to a major drought than to a minor drought.
Holistic	The mutual interaction between economic and environmental well-being should be modeled (Constas and Barrett, 2014).
Flexible	Households, even those living in similar contexts, may follow very different post-shock recovery pathways. Thus, the heterogeneity of response capacities should be taken into account.
Clearly communicable	The framework and the metric should be intuitive.
Scale invariant	Comparison across countries should be possible and not be dependent on the local currency or inflation.
Cardinality	The measure should allow individuals to be ranked in terms of resilience, and should allow comparisons among individuals, distinguishing *by how much* one is more or less resilient than another.
Orthogonality	The measure should be independent of measures of other dimensions of wellbeing, such as poverty and vulnerability. This ensures that estimates are valid, allows impact evaluation, and permits testing of the relationship between resilience, poverty and vulnerability.

APPENDIX C: SPEI COMPUTATION

The calculation of the SPEI has four main steps. Here, we follow the presentation of Vicente-Serrano et al. (2010). The first step consists in computing potential evapotranspiration (PET), i.e. the *demand* for water in the hydrological process. The simplest PET index is the Thornthwaite index [63]: it requires only the temperature and the latitude at which the data have been gathered.

The second step consists in computing the climatic water balance for month t, i.e. the difference between precipitation and evapotranspiration:

$$D_t = P_t - PET_t$$

where D, P and PET are the climate balance of water, the precipitation and the potential evapotranspiration measured in millimeters, respectively. A positive value for D_t means that there is a water surplus at time t, while a negative value implies a water deficit.

The third step consists in fitting a distribution F(D) on the observations gathered over the sample period. The longer the period, the better fit of the distribution, but 30 years of data, i.e. 30 observations of D_t, is deemed acceptable. Several candidate distributions were investigated by Vicento-Serano et. al: Pearson III, Lognormal, Log-logistic and General Extreme Value, and were found to fit well with empirical probabilities. As such, the selection among them is based on their behavior at most the extreme value. The log-logistic distribution is therefore preferred, and its parameters are estimated with the unbiased Probability Weighted Moments method [44].

The last step consists of standardizing the fitted distribution. This is done via the classic approximation of Abramovitz and Stegun (1965):

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}$$

where $W = \sqrt{-2 \ln P}$ for $P < 0.5$, where P is the probability of exceeding a determined D value: $P = 1 - F(x)$. If $P > 0.5$, then P is replaced by $1 - p$ and the sign of the resultant SPEI is reversed. The constants are $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

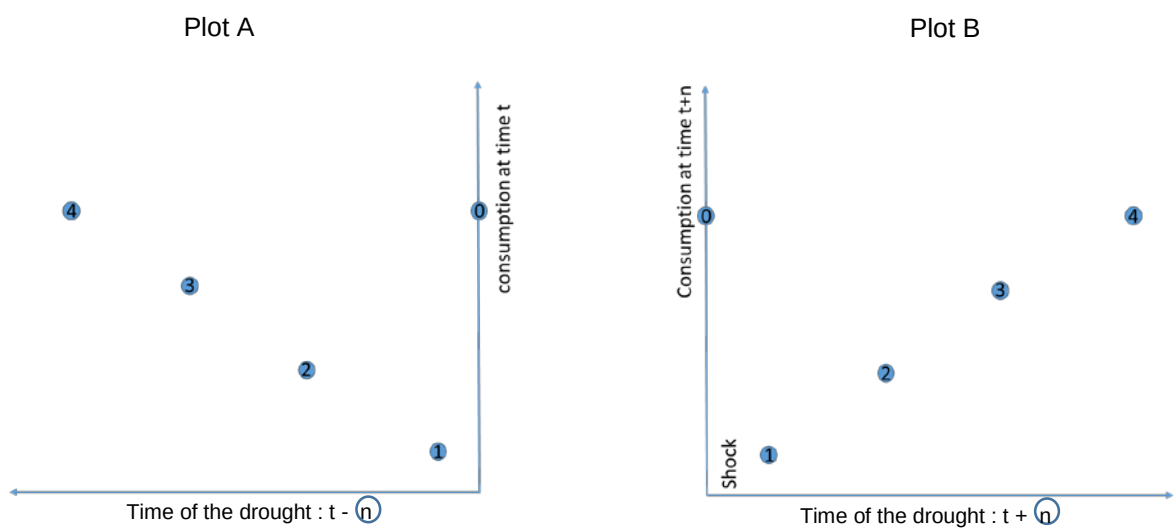
APPENDIX D: THE DLNM MODEL, AN INTUITIVE EXPLANATION

Instead of considering initial weather conditions and future consumption, we consider past weather conditions and present consumption. In other words, by understanding how past weather events have affected current consumption, we can project forward to assess how current weather will affect future consumption over time.

In order to introduce the framework, let us consider Plot A on Figure 12 where the horizontal axis is the timing of a weather shock (1 to 4 years ago) and the vertical axis is its effect on *current* consumption. Let us imagine five exclusive scenarios, which is depicted in

> Scenario 0: No drought occurred in the survey year. Dot 0 in Plot A represents the household's normal consumption levels.
>
> Scenario 1: A drought occurred in the year preceding the survey. We expect current consumption to be far below normal, represented by dot 1 in Plot A, as households are likely in the early stages of coping with the shock.
>
> Scenario 2: A drought occurred two years before the survey. We expect current consumption to be lower than normal but higher than in scenario 1, as households would have had longer to recover. See dot 2 in Plot A.
>
> Scenario 3: A drought occurred three years before the survey. We expect current consumption to be lower than normal but higher than in scenario 2, as households would have had longer to recover. See dot 3 in Plot A.
>
> Scenario 4: A drought occurred four years before the survey. If the household is resilient, at some point, the drought will be fully absorbed and current consumption will have recovered to normal consumption levels: dot 4 as dot 0 on plot A.

Figure 12: Illustration of the backward and forward perspectives on model with lags

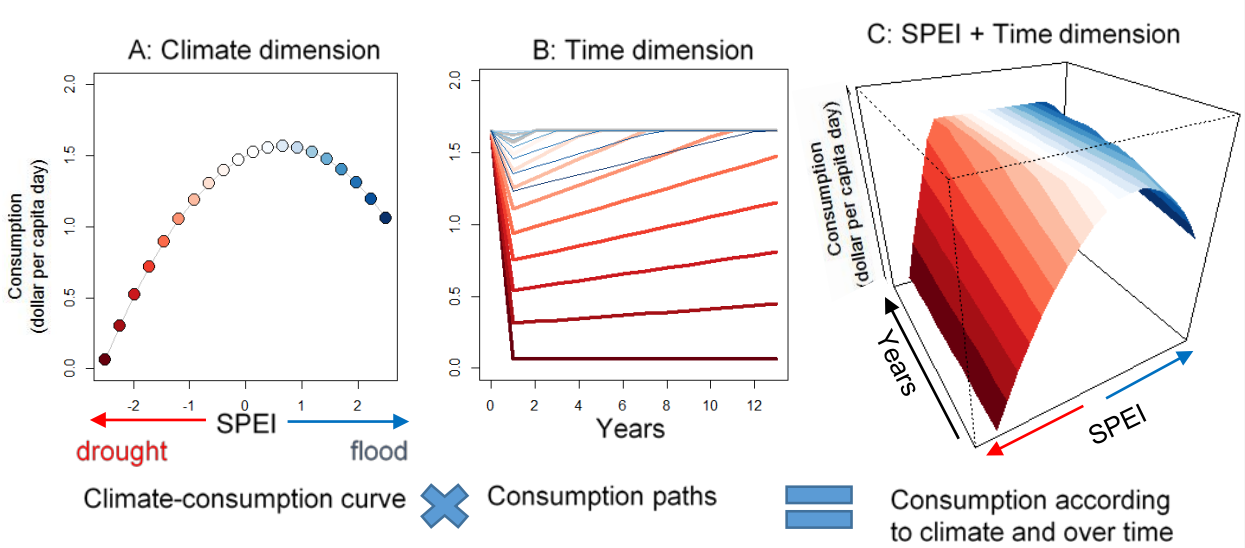


Once the dynamic properties of the relationship between droughts and current consumption have been mapped out, as shown in Plot A, we can apply this understanding to project forward, assessing future consumption levels given a current drought. This essentially involves mirroring the graph from plot A onto plot B. For instance, if there is a drought at time 0, consumption in the next period is likely to be at the same level as consumption under Scenario 1, represented here by the sharp decline. Similarly, consumption in period 2 is likely to be at same level as under Scenario 2, and period 3 consumption will

mimic Scenario 3. As in the backward-looking model, the household will be expected to be back on its feet by period 4. This insights allows us to measure the effects of a recurrent, or a *double-bang* shocks. For instance, if a household was hit by a shock in both period 1 and period 2, the effect can be calculated by simply adding the consumption shortfall from scenarios 1 and 2.This approach corresponds to a standard distributed lag *linear* model.

The effect of SPEI is however *non-linear*: consumption peaks in normal weather conditions and decrease in case of excess moisture or drought. In order to take this into account, we need a distributed lag *non-linear* model (DLNM) [8, 9]. In the DLNM model, both the non-linear link between consumption and SPEI, i.e. the exposure dimension, and the rate at which the effect of a given SPEI shock fade over time, i.e. the lag structure, are estimated. We can hence simultaneously estimate the recovery slope for a given sets of events and the climate-consumption curve.

Figure 13: Illustration of the forward perspective on the DLNM model



Plot A shows the climate-consumption curve of a representative household in time t+1, given weather conditions at time t.

Plot B shows a set of recovery paths for a large variety of potential shocks. The line colors correspond with the dots in Plot A: red lines correspond with consumption paths resulting from drought-related shocks while blue lines correspond with consumption paths resulting from shocks of excess moisture. We can see that the representative household takes more time to recover from large shocks than from small shocks. Similarly, it recovers more quickly from small droughts than from floods of equal magnitude.

Plot C combines the two dimensions to summarize the overall approach. Looking solely at the SPEI-consumption dimension, one recognizes the familiar inverted U-shape of the climate-consumption line from Plot A. Looking at the time-consumption dimension, one recognizes the familiar post-shock recovery paths shown on Plot B. The DLNM provides an estimation of the surface shown on plot C.

Figure 13 gives an illustration. On plot A, we show the exposure dimension in the first time period, i.e. the relationship between SPEI and climate. On plot B, we show the time dimension, i.e. how consumption is expected to evolve given a weather shock in period 1. Plot B of Figure 13 is a replication of plot B in Figure 12, except we add here the recovery trajectory for all the types of weather shocks represented on plot A. We see for instance that a household is more vulnerable and less resilient to a large drought than to excess moisture because, respectively, the red dots on plot A are below the blues ones and, on plot B,

recovery is longer after a drought (red lines) than excess moisture (blue line). The DLNM model allows hence the estimation of both vulnerability and resilience scores. Lastly, plot C combine the both dimensions. One recognize the familiar inverted U curve of the climate consumption curve by looking at the SPEI-consumption dimension and the recovery slopes by looking at the time-consumption dimension. This put us in position of estimating the cumulative effect of all categories of weather shocks over time.

The DLNM model estimate consumption dynamics by relying on the history of weather event instead of requiring repetitive measurement of consumption over time. The approach offers three main advantages over an approach based on repetitive measurement of consumption. First, it allows for more timely resilience assessments. Given baseline data, we can produce ex-ante estimates of the expected recovery time for any type of weather shock. Second, it limits data requirements and decreases costs. Rather than needing to implement expensive household surveys every year and implement rapid assessments on short notice, we can link just one cross-section of a survey to historical weather data which are freely available at a small scale resolution for the entire globe from at least the beginning of the 1980's. Finally, it allows us to measure the effects of recurrent, or *double-bang* shocks.

APPENDIX E: THE DLNM MODEL IN MORE DETAIL

We follow here very closely the derivation presented in [8]. Interested readers are encouraged to look at the original paper.

Let us start by introducing the linear lag model before extending to the non-linear case. Assuming that the effect of SPEI is linear, the relationship between current consumption and a given drought in the past can be modelled as:

$$c(s,t) \approx \sum_{l=l_0}^{L} s_{t-l} w(l)$$

where is consumption at time t, s_{t-l} is the SPEI condition at time $t-l$, $w(l)$ is the lag response function modelling the curve association with exposure to SPEI at lag l and the approximation comes the treatment of the lag structure as discrete rather than continuous.

For estimating the lag response function, we can express it a linear combination of terms obtained through basis transformation. Let us first define the vector of SPEI exposure history as:

$$\boldsymbol{q}_{S,t} = \left[s_{t-l_0}, \dots, s_{t-l}, \dots, s_{t-L}\right]^T$$

We can then re-expressed $c(s,t)$ in matrix notation as:

$$c(s,t;\boldsymbol{\eta}) = \boldsymbol{q}_{s,t}{}^T \boldsymbol{C}\boldsymbol{\eta} = \boldsymbol{w}_{s,t}^T \boldsymbol{\eta}$$

where the $(L-l_0+1) \times v_l$ matrix $\boldsymbol{C}$ is obtained from the transformation of the lag vector $\boldsymbol{l} = [l_0, \dots, l, \dots L]^{\boldsymbol{T}}$, by choosing a specific basis with dimension v_l for the lag response function $w(l)$, which defines the related basis function. The function $c(s,t;\boldsymbol{\eta})$ is hence represented as a lag basis function with parameters $\boldsymbol{\eta}$.

The extension to the non-linear case require first the definition of an exposure function. In our case, this corresponds to the familiar inverted U shape of the climate consumption curve, on at each of the lags considered in the model. Following Gasparrini (2014), the derivation is presented in terms of general exposure function $f()$:

$$c(s,t) \approx \sum_{l=l_0}^{L} f.w(s_{t-l}, l)$$

where $f.w(s_{t-l}, l)$ is a bi-dimensional *exposure-lag function*. The simpler basis-lag function has to be extended by choosing additional basis with dimension v_s for representing$f()$, resulting in a $(L-l_0+1) \times v_S$ matrix $\boldsymbol{R}_{s,t}$. Letting:

$$\boldsymbol{A}_{s,t} = \left(\boldsymbol{1}_{v_s v_l}^{\boldsymbol{T}} \otimes \boldsymbol{R}_{s,t}\right) \odot \left(\boldsymbol{C} \otimes \boldsymbol{1}_{v_s}^{\boldsymbol{T}}\right)$$

$c(s,t)$ can be expressed as a cross-basis matrix can be expressed as:

$$c(s,t;\boldsymbol{\eta}) = \left(1_{v_s v_l}^T \boldsymbol{A}_{x,t}\right)\boldsymbol{\eta} = \boldsymbol{w}_{s,t}^T \boldsymbol{\eta}$$

The dimensions of the cross-basis matrix is expressed in terms of the time and the SPEI dimensions.

APPENDIX F: DLNM ESTIMATION

Despite the complexity of the DLNM model, the R package dlnm greatly simplifies the estimation and plotting of results[64]. The exposure dimension and time dimension were expressed respectively as a quadratic function and a decay function:

$$f(s_{t-l}) = \beta {s_{t-l}}^2$$
$$w(s_{t-l}) = e^{-s_{t-l}/\gamma}$$

where the scale parameter γ is defined before the estimation and the parameter β is estimated and the number of lags was set to 15. While the parameters β determines the curvature of the climate consumption line, the parameter γ determines the rate of decay of the effect of any given weather shock. The optimal scale parameter γ was chosen minimizing the AIC score obtained in different regressions where γ is left to vary. Results are reported on table for the three datasets are shown on Table 11.

Table 11: DLNM, specification tests

	LSMS			ERHS			ENBCCA		
Best models	**AIC**	β	γ	**AIC**	β	γ	**AIC**	β	γ
1	5895	-0.04	1	3681	-0.08	2	3393	-0.08	1
2	5902	-0.02	2	3683	-0.11	1	3396	-0.05	2
3	5908	-0.02	3	3684	-0.02	9	3404	-0.03	3
4	5909	-0.01	11	3684	-0.02	10	3410	-0.02	4
5	5909	-0.01	12	3684	-0.02	11	3413	-0.01	5

We also conducted the selection of the model on more flexible relationship and by letting the number lags vary. In all cases, smallest AIC scores were obtained with 15 years of lags. More testing is however required to use these more flexible models.

APPENDIX G: COMPUTATION OF THE INDICES

Let us express consumption as a quadratic function of SPEI:

$$c = g(S, \beta) = \beta_0 + \beta_1 S + \beta_2 S^2$$

where c is consumption, S is SPEI and β_i are parameters. β_1 and β_2 determine the sensitivity to climate; if they are equal to zero, consumption is not sensitive to climate and stays at β_0 regardless of the weather conditions. This would correspond to a horizontal consumption line on Figure 1. By contrast, non-zero values for β_1 and β_2 imply that consumption varies with weather conditions.

Based on the β parameters, we can derive the consumption levels under different weather scenarios and hence compute the climate-induced vulnerability index (for example, for a 10 years' return drought):

$$V_{w,t} = \left(\frac{z - c(-1.3)}{z}\right) I(c(-1.3) < z) - \left(\frac{z - \beta_0}{z}\right) I(\beta_0 < z)$$

where the SPEI value of -1.3 corresponds to a 10 years' return drought and z is the poverty line, $I()$ is an indicator function equals to 1 if the condition is satisfied and zero otherwise, and:

$$c(-1.3) = \beta_0 + \beta_1(-1.3) + \beta_2(-1.3)^2$$

Note that the consumption under normal conditions equals β_0 as SPEI=0 under normal conditions. The index can be expressed more succinctly as:

$$V_{w,t}(s_t) = \Delta_{s_t} FGT_{t+1}$$

where FGT_{t+1} is the expected poverty gap and Δ_{s_t} is the difference operator over a shock s defined in terms of the SPEI.

For a household below the poverty line under normal weather conditions, we have:

$$V_{w,t}(s_t) = -\frac{\beta_1 s_t}{z} - \frac{\beta_2 {s_t}^2}{z}$$

As the climate vulnerability index is the average weather vulnerability index, it solves to:

$$V_{C,t}(s_t) = E\left(-\frac{\beta_1 s_t}{z} - \frac{\beta_2 {s_t}^2}{z}\right)$$
$$= -\frac{\beta_2}{z}$$

where the expectation, E, is taken over the distribution of the SPEI, a standard normal distribution.

For the climate vulnerability score of household above the poverty line under normal condition, the simplest is to rely on simulation. We will provide in future work an analytical expression of the index in terms of the parameters of the model.

For the weather resilience index, we simply identify the first observation crossing in the fitted lags DLNM model where the SPEI has no effect. See Appendix D and E for the details on the DLNM model.

APPENDIX H: APPLICATION TO DYNAMIC RISK ANALYSIS

In order to provide a framework for resilience analysis, Barret and Constas [14] proposed to summarize the stochastic well-being dynamics through the moment functions for conditional well-being:

$$\mu_k(W_{t+s}|W_t, R_t, \varepsilon_t) \tag{1}$$

where μ_k represents the kth moment—for example, the mean (k = 1), variance (k = 2), or skewness (k = 3), W_t the well-being at time t, R_t the state of the natural resources and ε_t and a disturbance term capturing all shocks not related to natural resources (illness related death of the household head for instance).

The climate consumption-curve in the single period model provides:

$$m^k(c_{t+s}|\, S_t, \varepsilon_t) \tag{2}$$

where S is the SPEI, i.e. the net balance of water in the agro-ecological system, which can serves as a good proxy for R_t, and c_{t+s} is consumption, a proxy of well-being.

Indeed, letting:

$$c = \beta_0 + \beta_1 S + \beta_2 S^2 \tag{3}$$

$$= a(S - B)^2 + D \tag{4}$$

where $a = \beta_2$, $B = -\beta_1/2\beta_2$, $D = \beta_0 - (\beta_1/2\beta_2)^2\beta_2$ and $(S - B)^2$ follows a noncentral chi-squared distribution with 1 of degree of freedom and noncentrality parameter $\lambda = (-B)^2$. It follows that c is a linear transformation of a non-central chi-squared distributed random variable.

Taking this into account and substituting the original parameters back in, the first four central moments of c are given by:

$$\mu_1(c) = \beta_0 + \beta_2 \tag{5}$$

$$\mu_2(c) = 2\beta_2^2 + \beta_1^2 \tag{6}$$

$$\mu_3(c) = 8\beta_2^3 + 6\beta_2\beta_1^2 \tag{7}$$

$$\mu_4(c) = 48 + 12\beta_2^4 + 6\beta_1^4 + 96\beta_1^2\beta_2^2. \tag{8}$$

We can also obtain the cumulative distribution function (CDF), $F_c(c)$, by letting:

$$c = H^2 + D \tag{9}$$

where $H = \sqrt{a}(S - B)$ and writing:

$$\begin{aligned} F_c(C) &= P(c < C) = P(H^2 + D < C) = P(H^2 < C - D) \\ &= P\left(|H| < \sqrt{C - D}\right) = P\left(-\sqrt{C - D} < H < \sqrt{C - D}\right) \qquad if\ C \geq D \\ &= P\left(-\frac{\sqrt{C - D}}{\sqrt{a}} - \frac{\beta_1}{2\beta_2} < \frac{H}{\sqrt{a}} - \frac{\beta_1}{2\beta_2} < \frac{\sqrt{C - D}}{\sqrt{a}} - \frac{\beta_1}{2\beta_2}\right) \quad if\ C \geq D \\ &= P\left(-\frac{\sqrt{C - D}}{\sqrt{a}} - \frac{\beta_1}{2\beta_2} < T < \frac{\sqrt{C - D}}{\sqrt{a}} - \frac{\beta_1}{2\beta_2}\right) \qquad if\ C \geq D \end{aligned} \tag{10}$$

where $T = \frac{H}{\sqrt{a}} - \frac{\beta_1}{2\beta_2} \sim N(0,1)$.

We have hence:

$$F_c(C) = \Phi\left(\frac{\sqrt{C-D}}{\sqrt{a}} - \frac{\beta_1}{2\beta_2}\right) - \Phi\left(-\frac{\sqrt{C-D}}{\sqrt{a}} - \frac{\beta_1}{2\beta_2}\right) \quad if\ C \geq D\ and\ 0\ otherwise \tag{11}$$

where Φ is the cumulative normal distribution function.

Lastly, we can specify consumption not only as a function of SPEI, but also as a function of other key determinants such as land tenure, agro-ecological zone, development intervention, etc. In order to better assess the effect of the latter variables on climate risk exposure, we specify the following function:

$$g(S, G, \beta) = \beta_0 + \beta_1 S + \beta_2 S^2 + \beta_3 G + \beta_4 GS + \beta_5 GS^2 \tag{12}$$

where G is the added variable of interest, for instance a dummy variable for household benefiting from a food for work intervention. Solving this quadratic equation, the inverse function of $g(S, G, \beta)$ and its derivative in absolute terms are:

$$g(c)_k^{-1} = \frac{-(\beta_1 + \beta_4 G) \pm \sqrt{(\beta_1 + \beta_4 G)^2 - 4(\beta_2 + \beta_5 G)(\beta_0 + \beta_3 G - c)}}{2(\beta_2 + \beta_5 G)} \tag{13}$$

and

$$\left|\frac{dg_k^{-1}(c)}{dc}\right| = \frac{1}{\sqrt{(\beta_1 + \beta_4 G)^2 - 4(\beta_2 + \beta_5 G)(\beta_0 + \beta_3 G - c)}}. \tag{14}$$

Equations 26 and 27 are then inserted into equation 12 in order to obtain $f_c(c)$, from which we can easily derive the central moments.

Similarly, expressing c as:

$$c = \alpha(S - \mathrm{B})^2 + \Theta \tag{15}$$

where $\alpha = \beta_2 + \beta_5 G$, $\mathrm{B} = \frac{-\beta_1 - \beta_4 G}{2(\beta_2 + \beta_5 G)}$ and $\Theta = \beta_0 + \beta_3 G - \left(\frac{-\beta_1 - \beta_4 G}{2(\beta_2 + \beta_5 G)}\right)^2$, we can express the CDF of c for given value of G value as:

$$F_{c|G}(C) = \Phi\left(\frac{\sqrt{C-\Theta}}{\sqrt{\alpha}} - \frac{\beta_1 + \beta_4 G}{2(\beta_2 + \beta_5 G)}\right) - \Phi\left(-\frac{\sqrt{C-\Theta}}{\sqrt{\alpha}} - \frac{\beta_1 + \beta_4 G}{2(\beta_2 + \beta_5 G)}\right) \tag{16}$$

if $C \geq \Theta$ and 0 otherwise.

More research is needed to formally show that the extension to the multi-period model allows to obtain equation (1). We suggest it could be written as:

$$\mu_{1,t+1}(c) = \mu_{1,t}(c) + \beta_{2,t} \tag{17}$$

$$\mu_{2,t+1}(c) = 2\beta_{2,t}^2 + \beta_{1t+1}^2 \tag{18}$$

$$\mu_{3,t+1}(c) = 8\beta_{2,t}^3 + 6\beta_{2,t}\beta_{1,t}^2 \tag{19}$$

$$\mu_{4,t+1},(c) = 48 + 12\beta_{2,t}^4 + 6\beta_{1,t}^4 + 96\beta_{1,t}^2\beta_{2,t}^2. \tag{20}$$

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