Climate shocks, vulnerability, resilience and livelihoods in rural Zambia

Hambulo Ngoma, Arden Finn and Mulako Kabisa

Indaba Agricultural Policy Research Institute, Lusaka, Zambia; The World Bank, Poverty and Equity Global Practice, Washington, DC, USA

ABSTRACT
Climate and weather shocks pose risks to livelihoods in Southern Africa. We assess the extent to which smallholders are exposed to climate shocks in Zambia and how behavioural choices influence the negative effects of these shocks on vulnerability and resilience. We use household data from the nationally representative Rural Agricultural Livelihoods Survey and employ an instrumental variable probit regression model to control for the endogeneity of key choice variables. There are four main findings. First, droughts are the most prevalent climate shock faced by rural smallholder farmers in Zambia, but the extent of exposure differs spatially, with the Southern and Western Provinces being the hardest hit. Nationally, 76% of all smallholder farmers are vulnerable and only 24% are resilient, with female households most vulnerable. Second, increased climate shocks correlate with both increased vulnerability and reduced resilience, with short- and long-term deviations in seasonal rainfall worsening vulnerability and resilience. Third, higher asset endowments and education are correlated with reduced vulnerability and increased resilience. And last, climate-smart agricultural practices significantly improve household resilience. These findings imply a need to support scaling of climate-smart agricultural technologies and to invest in risk mitigation strategies such as weather-indexed insurance and targeted social cash transfers.

1. Introduction
As in other countries in Sub-Saharan Africa (SSA), both the frequency and intensity of climate and weather shocks are increasing in Zambia, pushing rural households – especially smallholder farmers – into poverty (Al Mamun et al., 2018; Braimoh et al., 2018; Ngoma et al., 2019; Ngoma et al., 2021; Thurlow et al., 2012). It is estimated that climate variability reduced growth in Zambia’s agricultural Gross Domestic Product (GDP) and national GDP by 4% and 10%, respectively, between 2006 and 2016 (Thurlow et al., 2012), with an associated increase in the national poverty rate of 2%. In severe drought years, such as the 1991/1992 season, Thurlow et al. (2012) estimated that GDP reduced by 6.6% and poverty increased by 7.5 percentage points.

Climate change and variability are therefore important contributors to the high poverty incidence in rural Zambia which is estimated at 76.6% (CSO, 2015). Reliance on rainfed agriculture drives the high prevalence of poverty in rural Zambia, and among smallholder farmers. This dependence means that rural households are exposed to climate shocks. According to the 2015 Living Conditions Monitoring Survey (LCMS), poverty among small-scale farming households was 78.9% compared to 64.5% among medium-scale farmers (CSO, 2015). Poverty is highest in the Northern (79.7%), Eastern (70%), Southern (57.6%), and Central (56.2%) Provinces. Except for the Central and Northern Provinces, all have a higher population density than the national average, indicating a combination of high poverty rates and high absolute numbers of poor people.

Because rural households are not all the same, it is important to understand the extent to which different groups are exposed to and vulnerable to climate shocks. It is also important to assess the extent to which behavioural choices, such as adoption of climate-smart agriculture (CSA), might condition the negative effects of climate shocks on vulnerability and resilience. Apart from differences in geographic location, households also differ by socio-economic status, making some agricultural households systematically more exposed and vulnerable to climatic risk than others – for example, those primarily dependent on rainfed agriculture. In the same way, some households may be better equipped to reduce or build resilience before climate shocks occur or cope and adapt with them afterwards through adoption of sustainable or CSA farming practices such as conservation agriculture (CA).

Despite a growing body of literature linking climate risk, poverty, and livelihoods more broadly in Zambia, little attention has been devoted to carefully define and measure, and assess how the vulnerability and resilience of rural households varies by household type, geography, and wealth (Al Mamun et al., 2018; Alfani et al., 2019; Braimoh et al., 2018; Hamududu & Ngoma, 2019; Jain, 2007; Ngoma et al., 2019; Ngoma et al., 2021; Thurlow et al., 2012; Wineman & Crawford, 2017). It is equally not well understood the extent to which exposure to climate shocks, vulnerability, resilience and livelihoods in rural Zambia
different climatic shocks affects vulnerability and resilience at national and subnational levels. There is also a dearth of information on the relative importance of CSA practices such as minimum tillage, improved inputs (fertilizer and seed), and crop diversification as means to offset the effects of climate shocks on livelihoods. We focus on both vulnerability and resilience as key livelihood indicators. This paper contributes towards filling these gaps and evaluates the common types of climate shocks Zambian rural households face and how these shocks affect household vulnerability and resilience. It also assesses the types of strategies households use to cope with shocks. In particular, we assess if CSA practices can mediate the effects of climate shocks on vulnerability and resilience.

The multidimensionality of poverty, resilience and vulnerability and their causes makes measuring any of these indicators a challenging task. For this paper and given our focus on the last two metrics, we follow Barrett and Constanas (2014) and define resilient households over three waves of data as those that were never poor or those that escaped poverty by the third wave. We classify vulnerable households as those that are poor in all the three waves, or poor in the first and third waves but not in the second wave, or those poor in the second and third waves but not in the first wave, or indeed those that were not poor in the first and second waves but fell into poverty in the third wave. Vulnerable households are more likely to be adversely affected due to either exposure or lack of capacity to cope and adapt. Exposure refers to the presence of rural households or economic activities in places or areas that are more likely to be negatively affected by climate shocks.

The data used in the analysis are from the nationally representative Rural Agricultural Livelihood Surveys (RALS) conducted in 2012, 2015, and 2019 in Zambia. Although the full dataset is a three-wave panel, most of our estimating equations are cross-sectional, as we have assigned a vulnerability and a resilience status to each household based on movements in and out of poverty between the first and third waves. To give a medium-term perspective, we only considered outcomes in the final wave. In this way, households are only classified as vulnerable or resilient at the third wave. It is possible that households may switch back and forth between 2012 and 2019 as their poverty status changes. Because a stable measure of vulnerability and resilience should span multiple years, we restrict our empirical models to observations realized in the third wave in a cross-sectional sense. The poverty metric used in this paper is based on total household income captured in RALS. For our poverty estimates to be comparable to those based on consumption expenditure, we used the RALS 2015 data to determine an income threshold or ‘poverty line’ that would make the income-based poverty rate equal to the expenditure-based rural poverty rate estimated in the 2015 Living Conditions Monitoring Survey (LCMS) in Zambia.

We extend the literature on climate change and poverty in Zambia in four ways. First, we take advantage of the detailed three wave longitudinal household-level data to analyse the types of climate shocks households face in rural Zambia, how these shocks differ by geography and household types, and how these shocks affect vulnerability and resilience over time. This builds on several papers that focus on explaining poverty dynamics in Zambia. See for example Chapoto et al. (2011) covering the period 2001–2008, Ngoma et al. (2019) for the period 2012–2015 and Diwakar et al. (2020) for the period 2012–2019. The last two papers use the same RALS data sets as in this paper but differ from this study in the sense that they focused on poverty dynamics. Besides our focus on resilience and vulnerability, the use of an income-based poverty line that equates the 2015 poverty rate in RALS to the expenditure-based poverty rate for that year is another major difference between this paper and others that use RALS data to study poverty dynamics in Zambia. Second, the paper incorporates unique exogenously defined drought and flood risks to measure vulnerability and exposure to climate risk. Third, we assess how exposure to climate risk affects vulnerability and resilience. And, last, we assess whether adopting common CSA practices mediates the effects of climate shocks on vulnerability and resilience in Zambia, and if so, by how much.

2. Climate shocks, vulnerability, resilience, and rural livelihoods: A brief review

The linkages between climate shocks, vulnerability, resilience, and livelihoods are complex. Climate change can increase poverty directly by reducing agricultural productivity and production, and by hindering asset accumulation and returns on assets. Indirectly, climate change affects poverty through output prices, labour productivity and the availability of off-farm employment opportunities. This paper focuses primarily on the direct livelihood effects. Zambia has witnessed an increase in the incidence of climate shocks such as droughts, seasonal and flash floods, extreme temperatures, and dry spells. These weather extremes have significant knock-on side effects on rural farmers who depend on rainfed agriculture for their livelihoods. Ahmed et al. (2009) predict that by 2080, climate change will increase the intensity of dry spells and subsequently worsen the incidence of poverty among smallholder farmers by 4.6 percentage points in all agro-ecological regions in Zambia. Average temperatures are predicted to rise by between 1.9 and 2.3 degrees Celsius, and annual rainfall is projected to reduce by up to 3% by 2100 in Zambia (Petrie et al., 2018a; Hamududu & Ngoma, 2019). The locus of these changes and the worst negative impacts are concentrated in Southern and Western Provinces of Zambia (Ngoma et al., 2021). These climatic changes are projected to reduce resilience and increase vulnerability of agro-based livelihoods that rely on rain-fed production (Matata et al., 2023; Ngoma et al., 2021). The effects are gendered such that female-headed households tend to be the most vulnerable and least resilient in Eastern and Southern Africa, and Zambia (Rahut et al., 2021; Umar, 2021)

Other studies demonstrate the linkages between climate shocks and livelihoods. For example, in a cross-country study, Al Mamun et al. (2018) found that the El Niño weather phenomenon worsened poverty in Eastern and Southern Africa, noting that a 10% reduction in maize yields increases the national poverty rate by 1 percentage point and the poverty gap by 1.9 percentage points in Zambia. The 2015/2016 El Niño was associated with severe droughts and floods in different parts of Zambia. Alfani et al. (2019) found that the 2015/
2016 El Niño-induced drought shocks in Zambia were associated with about 20 and 37% reduction in maize yields and per capita incomes, respectively. Climate shocks such as droughts and floods at the national level reduce cotton production by an estimated 68%, and both maize and groundnuts by 33% in Zambia (Braimoh et al., 2018). Relating these results to livelihoods suggests that El Niño is likely to increase vulnerability and reduce resilience.

Although it is generally believed that climate and weather shocks have the potential to worsen poverty and vulnerability while eroding resilience, it remains unclear how impacts vary across Zambian household types and regions, and the extent to which the poor are exposed to weather shocks. While CSA technologies have the potential to raise productivity and help farmers adapt to climate shocks, results from adopting CSA have been mixed in different contexts. This is not surprising because what is CSA in one context might not be so in another context and no single practice is CSA all the time and everywhere (Mwongera et al., 2017). On the positive side, Thierfelder et al. (2017) conclude their review of CSA in SSA by stating that CSA principles such as conservation agriculture (CA) have positive effects on adaptation and productivity but lags of two to five cropping seasons are common before yield benefits become significant. Similarly, Michler et al. (2019) found that although CA did not confer any yield benefits, it helped farmers adapt to rainfall variability in Zimbabwe. Results from the research programme on climate change, agriculture, and food security (CCAFS) Kaffrine Climate-Smart Village also showed that farmers were able to enhance resilience and reduce vulnerability by adopting a suit of CSA practices, including the use of inorganic fertilizers (Bonilla-Findji et al., 2020). Based on the foregoing, it can be surmised that CSA can reduce vulnerability and enhance resilience in given contexts. Some CSA practices, in particular crop diversification, commercial horticulture, agroforestry and reducing post-harvest loss are associated with positive long-term effects on household welfare in Zambia (World Bank, 2018).

The effects of CSA are all not positive. For example, Corbeels et al. (2020) found that CA only confers small yield gains over conventional agriculture in 16 SSA countries and conclude that ‘CA may not be the technology for African smallholder farmers to overcome low productivity and food insecurity in the short-term’. The missing link from the foregoing is an assessment of the extent to which CSA practices mediate vulnerability and resilience to climate shocks using multi-year household data as such data allow for better measurements of outcomes during and after shocks.

3. Conceptual framework

The theoretical underpinning to study how different shocks and stressors affect livelihoods can be linked to literature on the economics of poverty traps (Barrett & Carter, 2013) or what is generally called the human capabilities framework (Barrett & Constas, 2014). The central idea is to study the stochastic dynamics of well-being that individuals go through to avoid or escape from poverty traps. Because there are now more stressors and shocks that are less predictable that households face (Barrett & Constas, 2014), it is of policy interest to understand how to ameliorate the negative consequences. How households respond to these shocks ex-post determines whether they are resilient or vulnerable.

A classic example is climate shocks – both floods and droughts – that present a risk to rural livelihoods in Zambia given that over 90% of smallholder agriculture depend on rainfed production systems (Wineman & Crawford, 2017). Climate shocks affect smallholder farmers in diverse ways depending on the farmer’s asset base, socioeconomic status, social capital, capabilities, and coping capacities. Reduced agricultural productivity and output are the main negative effects of climate shocks on rural livelihoods, which in turn lead to reduced incomes and consumption (Karfakis et al., 2012; Skoufias & Vinha, 2012). The effects may be severe for poor households with little or no assets or savings to fall back on in the event of climate-induced agricultural production losses. Asset-poor households are generally less resilient and more vulnerable. On the other hand, asset-rich households or those with savings might be less affected by climate shocks because they can liquidate their assets and/or use savings to smooth consumption and avert food and income insecurity. To achieve a more nuanced understanding of how climate shocks impact livelihoods, it is important to classify households into sub-groups that differ based on vulnerability and resilience.

Climate shocks could increase household vulnerability and reduce resilience through various pathways. Weather and climate variability affect rural household consumption and incomes, especially for those who depend on rainfed agriculture for their livelihoods. In the event of disruptions to agricultural production, poor households are likely to intensify extraction of natural resources and to engage in non-farm employment (Angelsen & Dokken, 2018; Mulenga et al., 2014). Increased natural resources extraction, such as charcoal production and logging engender environmental degradation, which disproportionately affects smallholder farmers. Moreover, intensification of environmentally degrading livelihood activities can aggravate poverty for households whose livelihoods depend on these natural resources.

Households with a higher asset base could liquidate some to help smooth income and consumption, but this is only a temporary coping strategy. If climate or weather shocks persist for a longer period, households may deplete their assets and savings, causing a further slide into poverty. Repeated occurrences may lead to a poverty trap. Without formal insurance or social protection, this creates a vicious cycle in which climate shocks increase poverty and environmental degradation that create more climate shocks. Households may also use incomes earned from non-farm employment to smooth consumption in places where such work is available. The outcome will either be vulnerability or resilience, depending on whether (i) a household stays or becomes poor, or (ii) was never poor or escaped poverty.

4. Data and methods

4.1. Data sources and sampling

We draw on data from the three-wave, nationally representative RALS survey conducted by the Indaba Agricultural Policy
Research Institute (IAPRI) in collaboration with the Ministry of Agriculture and the Central Statistical Office (CSO) in Zambia. The 2010 census of population and housing provided the sampling frame for the first survey wave in 2012. A three-stage sampling scheme was used to select households for interviews. In stage one, enumeration areas with at least 30 agricultural households were selected from the census using proportional to size sampling approaches. Stage two conducted a complete listing of households in each of the selected enumeration areas. The purpose of the second stage was to identify agricultural households. Households were selected for interview in the third stage. To do so, agricultural households identified from stage two were stratified into three classes based on (i) area under crops; (ii) presence of special field crops, and (iii) the number of cattle, goats and chickens raised. About 20 households distributed across the three strata per enumeration area were then selected using systematic random sampling. Additional details on sampling and survey design can be found in CSO/MAL/IAPRI (2012) and CSO/MAL/IAPRI (2015).

The RALS surveys collected data from 8,839 households in May/June 2012; 7,934 in June/July 2015; and 7,241 in June/July 2019. This timing coincides with harvesting for the previous agricultural production season and the agricultural marketing season (from May year \( t \) to April year \( t+1 \)). All three RALS waves were designed to be statistically representative of the rural population at the provincial and national levels, and 6,531 panel households were successfully re-interviewed over the three waves.

We complemented survey data with geospatial decadal (10-day) rainfall data from the Climate Hazards Group Infra-red Precipitation with Station database (CHIRPS) for the period 1981–2018. Because RALS collected geocoordinates for each household, it was possible for us to use these to download and process past rainfall realizations for each household based on centroids for the past 30 years from the CHIRPS spatial data. In doing so, we merged rainfall variables with survey data from the RALS. CHIRPS is a quasi-global (50°S–50°N), with a 0.05° resolution that combines satellite and observation-based precipitation estimates (Funk et al., 2014). We used the decadal CHIRPS rainfall data to compute growing season rainfall spanning November of the previous year to March of the following year. We took advantage of the long time series to compute 30-year, long-term average rainfall, and long-term measures of rainfall variability such as the standard precipitation index (SPI), rainfall stress, and coefficient of variation.

### 4.2. Variables used in the main regressions

**4.2.1. Dependent variables**

This paper aims to explain the effects of climate shocks on vulnerability and resilience. We computed the poverty incidence using real household income deflated using consumer price indices (CPI) for the relevant survey years. We then estimated a level of real income that would equate the rural poverty rate in the 2015 RALS to the official national rural poverty rate reported in the 2015 LCMS. This gave us a national poverty line of ZMW 2,697 per adult, per year in 2015 kwacha. That is, a household is ‘poor’ if real per adult income is less than the threshold of ZMW 2,697 per year.9

We are also interested in understanding transitions in and out of poverty between 2012 and 2019. A household is chronically poor if it is recorded as being poor in all the three survey waves. A household that escaped poverty is one that was poor either in 2012 and/or 2015 but not in 2019, while a household entering poverty is one that was not poor in 2012 and/or 2015 but fell into poverty in 2019. It is worth noting that the preceding poverty transitions span a long period between 2012 and 2019 and that we are only able to observe poverty outcomes in the survey years. Thus, even if a household is observed as poor throughout the three waves, it is possible that such a household moved in and out poverty in the intervening years. Unfortunately, our data does not capture those transitions between survey years, so our observations reflect the minimum true extent of poverty mobility.

As stated before, our focus is not on explaining the drivers of poverty dynamics in Zambia, which are well captured in Ngoma et al. (2019) for the period 2012–2015 and Diwakar et al. (2020) for the period 2012–2019. We are interested in examining the correlates between climate shocks, CSA, vulnerability, and resilience. We define vulnerability and resilience in the spirit of Barrett and Constas (2014), and explicitly consider welfare movements in and out of poverty over the three survey waves. Vulnerable households are those that were poor in all three survey waves or those that fell into poverty by the third wave.10 A household is resilient if it was never poor in all three survey waves or escaped from poverty by the third wave.11 Because we can only observe whether a household is vulnerable or resilient at the third survey wave, we used covariates in the third wave and collapsed the three-wave panel data into cross-sectional data.

**4.2.2. Independent variables**

In addition to the usual socioeconomic and demographic factors that may influence whether a household is vulnerable and its level of resilience, we computed variables to measure rainfall variability and exposure to climate shocks. We computed a Standard Precipitation Index (SPI) that measures rainfall variability following Patel et al. (2007). Using 30-year spatial rainfall data, we computed the SPI as in Equation (1):

\[
SPI_{it} = \frac{(cagrain_{it} - \bar{cagrain}_{30})}{sdagrain_{30}}
\]

where \( SPI_{it} \) is the SPI for household \( i \) in year \( t \), \( cagrain_{it} \) is total rainfall for the agricultural season in year \( t \), \( \bar{cagrain}_{30} \) is the average annual rainfall over the last 30 years, and \( sdagrain_{30} \) is the standard deviation for seasonal rainfall over the last 30 years.

We adapt the approach of Azzarri and Signorelli (2020) and computed a drought risk variable that measures exposure to climate risk as rainfall that is less than the average seasonal rainfall at the enumeration area level minus two standard deviations of the enumeration area seasonal rainfall. We define flood risk as seasonal rainfall that is more than the average seasonal rainfall at the enumeration area level plus two standard deviations of the enumeration area seasonal rainfall. We measured rainfall variability using the coefficient of variation.
of the 30-year rainfall and a measure of rainfall stress. Following agronomic recommendations as implemented in Ngoma et al. (2015), we define rainfall stress as the number of consecutive 20-day periods with less than 40 mm of rainfall.\textsuperscript{12}

We also include 30-year average rainfall to measure the long-term effects, and the current growing season corresponding to the survey reference period to measure short-term effects. In addition to these climate shocks, we also control for CSA adoption, crop diversity,\textsuperscript{13} and access to credit, since these might influence how climate shocks affect vulnerability and resilience. We generate a binary proxy measure for CSA if a household used at least one or more of hybrid maize seed, inorganic fertilizer, and/or minimum tillage (MT).\textsuperscript{14}

Apriori, we expected a positive correlation between climate shocks and vulnerability, and a negative correlation between climate shocks and resilience. Table 1 defines the remaining variables. We chose all the variables used in the regressions based on the conceptual framework in section 2, drawing from several examples in the literature (see for example Al Mamun et al., 2018; Alfani et al., 2019; Azzarri & Signorelli, 2020; Braimoh et al., 2018; Jain, 2007; Ngoma et al., 2019; Thurlow et al., 2012; Wineman & Crawford, 2017).

4.3. Empirical strategy

Although the RALS is a longitudinal data set, vulnerability and resilience are defined as single states over all three waves. This implies that most of our estimation equations are cross-sectional rather than fully exploiting the panel dimension of the data. We estimate a probit regression model, as specified in Equation (2):

$$y_{ij} = \beta_0 + \text{ClimS}_i \beta_1 + X_i \beta_2 + \text{credit}_i \beta_3 + \text{CSAi} \beta_4 + \text{distmkt}_i \beta_5 + \text{Disti} \beta_6 + \mu_i$$

where $y$ is a $j^{th}$ dependent variable ($j =$ vulnerable or resilient) for household $i$; $\text{ClimS}$ is vector of exogenous climate shocks described above; $X$ is vector of socio-economic and demographic factors such as assets, crop diversity, age and education level of the household head; $\text{credit}$ is a dummy $=1$ if any household member obtained credit from any source; CSA is a dummy $=1$ if a household used any MT (ripping, basins, and/or zero tillage for main tillage on at least one plot), hybrid maize seed and inorganic fertilizer; $\text{distmkt}$ is the distance in kilometers from the homestead to the nearest main market; $\text{dist}$ is a dummy controlling for district-specific attributes such as topology and other things, and $\mu_i$ is the idiosyncratic error term. In addition to the variables in levels, we also include interactions between CSA and each of the climate shock measures to assess if adopting CSA influences the effects of climate shocks on outcomes.

4.4. Identification strategy

Proper identification of Equation (2) requires addressing the endogeneity\textsuperscript{15} of CSA adoption, crop diversity, and access to credit. Without this, the parameter estimates of the effects of climate shocks will be biased because these variables reflect

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**Table 1. Summary statistics of key variables used in the regressions.**

| Variable | Description | mean | SD  | n   |
|----------|-------------|------|-----|-----|
| Vulnerable | If poor in all the three survey waves or fell into poverty by the third wave in 2019 (yes = 1) | 0.76 | 0.43 | 6531 |
| Resilient | If never poor over the three survey waves, or escaped poverty by the third survey wave in 2019 (yes = 1) | 0.24 | 0.43 | 6531 |

**Independent variables**

- **Climate risk/exposure variables**
  - Drought risk (yes = 1)\textsuperscript{†} Seasonal rainfall < 2SD of 30-year average rainfall
  - Flood risk (yes = 1)\textsuperscript{†} Seasonal rainfall > 2SD of 30-year average rainfall
  - Seasonal rainfall November – March rainfall amount
  - 30-year average rainfall Average seasonal rainfall over 30 years
  - 30-year rainfall coeff. variation 30-year rainfall coefficient of variation
  - Standard precipitation index Current rainfall less 30-year average divided by 30-year SD
  - Rainfall stress Number of 20-day periods with < 40 mm of rain

- **Other independent variables**
  - Used CSA Used min till, hybrid maize seed or fertilizer (yes = 1)
  - Accessed credit (yes = 1) Accessed credit from any source
  - Crop diversity If Simpsons crop diversity index > median (yes = 1)
  - Asset index Asset index from PCA
  - femalehead Female head of household (yes = 1)
  - ageh Age of household head (years)
  - eduhed Education of household head (years)
  - dep_rat (Number of members aged < 14 + =>65)/# aged 15–64
  - mem0_5 # of members 0–5 years old
  - mem5_10 # of members 5–10 years old
  - mem10_15 # of members 10–15 years old
  - mem15_64 # of members 15–64 years old
  - farmsize Farm size (ha) less rented-and borrowed-in land
  - dmarket Distance to market (km)

**Instrumental variables**

- CSA-advice Received advice on aspects of CSA
- div-advice Received advice on crop diversity
- Mem-loan Member of a loan/credit group

\textsuperscript{†}reflect drought and flood indicators from spatial rainfall data. Results based on farmer perceptions for 2019 suggest that 63% and 12% of farm households encountered droughts and floods, respectively, on at least part of their farm.
farmer choices and may ‘co-determine’ the outcomes. For example, farmers that adopt CSA, have diversified crops, and accessed credit may be those with high intrinsic motivation so that they would likely be less vulnerable and more resilient even with climate shocks.

We used Wooldridge (2010)’s approach to control for endogeneity. This involved estimating a reduced form equation of the endogenous variable (CSA, crop diversity, and access to credit, separately) with instrumental variables (IVs) and the rest of the right-hand side variables, and then predicting generalized residuals, which are then included in the main outcome equations together with the endogenous variable(s). We instrumented CSA adoption using a dummy variable = 1 if a household accessed MT extension in the 2015 survey round, crop diversity with a dummy = 1 if a household received advice related to crop diversification, and access to credit using a dummy = 1 if anyone in the household is a member of a loan or savings group. We posit and test that access to CSA extension at t-1 is likely to increase CSA uptake in subsequent periods, as does membership to a loan or saving group for access to credit and access to information on diversification for crop diversity. These instruments are unlikely to affect outcomes directly except through their influence on the choice variables. Similar informational IVs have been used to study agricultural technology adoption in Africa, see for example Alem et al. (2015) and Ngoma et al. (2016). Because our main outcomes are realized after the third wave, we use covariates from the 2019 wave of the survey in a cross-sectional sense. As such, we do not control for time fixed effects.

The final estimable equation (Equation (3)) includes residuals for the CSA (CSAres), crop diversity (div_res) and access to credit (creditres) from the first stage regressions:

$$y_{ij} = \beta_0 + \text{ClimS}_i \beta_1 + X_i \beta_2 + \beta_3 \text{credit}_i + \beta_4 \text{CSA}_i + \beta_5 \text{CSAres}_i + \beta_6 \text{divres}_i + \beta_7 \text{credres}_i + \mu_i \tag{3}$$

5. Results and discussion
5.1. Exposure, vulnerability, and resilience among rural smallholders in Zambia

Droughts are the most prevalent climate shock that affected 65% of the rural smallholder farmers during the 2018/2019 season, particularly in Southern and Western Zambia (Tables S1, S2 and Figures S7 – S9). About 65% of farmers perceived a reduction in rainfall while 53% said temperature is increasing (Figure S1). At the national level, 76% and 24% of rural smallholder farmers were vulnerable and resilient, respectively (Figure 1). Eastern, Muchinga, Northern, and North-Western Provinces had, on average, a larger proportion of vulnerable households than the national average; while vulnerability in Southern, Western and Luapula hovered around the national average. Copperbelt, Central, and Lusaka Provinces had, on average, a larger proportion of rural households that were resilient than the national average (Figure 1).

These results on the prevalence of drought risk in Zambia are in line with Braimoh et al. (2018), who found that droughts are the main risk facing the agricultural sector in Zambia. Increasing rainfall variability in the country implies that some rural farm households are exposed and vulnerable to both droughts and floods, with significant differences across regions. Findings suggesting that a larger proportion of households experienced droughts and floods in Southern and Western Zambia is in line with Hamududu and Ngoma (2019) and Ngoma et al. (2021) who project worsened climate extremes and negative impacts of climate change on agriculture and livelihoods in these regions.

Further disaggregated results in Table S3 in the online appendix show that only about 19% of female-headed households were resilient compared to 25% for male-headed households. About 81% of female-headed households were vulnerable compared to 75% among male-headed households. When disaggregated by household types, about 80% of female adults-only households were vulnerable compared to 47% for male adults-only, and 77% for mixed male and female adult households. A smaller proportion of female adult-only households were less resilient at only 20% compared to 53% for male adult households, and 23% for both male and female adult households (Table S3). Thus, female-headed, and female adult-only households are more vulnerable and less resilient. Households that used CSA, as defined in this paper, were more resilient and less vulnerable, but the differences are small.

These findings are in line with Umar (2021) who found that female-headed households are most vulnerable and least resilient. While understanding why women led households are more vulnerable and less resilient is beyond the scope of this paper, we can speculate that this could related to the fact that women do not have access to the similar productive resources as do their male counterparts (FAO, 2011). If indeed, this is the case, and given societal expectations that women are in charge of taking care of the home, this predisposes women to climate shocks which reduces their resilience and worsens vulnerability.

We find that households transitioned in and out of poverty over the three survey waves in 2012, 2015, and 2019. At the national level, 46% of smallholder farmers were poor in all three survey waves in 2012, 2015, and 2019, while 2% were never poor (Figure 2). The rest of the farmers transitioned from being poor to non-poor status, or vice versa, over the three survey waves. For example, 13% of smallholders that were not poor in 2012 fell into poverty in 2015 and 2019, and about 14% of smallholders that were poor in 2012 and 2015 escaped poverty in 2019. About 3% of smallholders transitioned from being poor in 2012 and escaped poverty in 2015 and 2019. Nearly one-tenth of smallholder farmers were poor in 2012 and 2019 but not in 2015, and about 4% were poor in 2015 but not in 2012 and 2019. These transitions in and out of poverty define chronic and transitory poverty (Figure 3). A household that was poor in all three survey waves is chronically poor, while one that was poor in all waves was never poor. A household is transient poor if it was poor in one or two survey waves.

About 74%, 24% and 2% of rural households were chronically, transient, and never poor in 2019 in Zambia (Figure 3) From the foregoing, and on average, the proportions of vulnerable and resilient households in Zambia’s Southern and
Western Provinces are qualitatively similar to the national averages. However, there were more vulnerable households in Eastern, Muchinga, Northern, and North-western provinces than the national average. Copperbelt, Lusaka, and Central provinces had larger proportions of resilient households. These findings call for tailored and targeted agricultural development interventions to help farmers adapt to observed and projected weather changes. While droughts are a major climate shock or risk to agricultural production and livelihoods in Zambia, our findings suggest that floods are an important risk. Thus, risk mitigation and management require strategies to address both droughts and floods in smallholder agriculture.

5.2. Climate shock impacts on vulnerability and resilience in rural Zambia

Table 2 presents annotated outputs from the first stage probit regressions where we test and confirm that each of the candidate IV strongly correlates with a given endogenous variable. Two of the three IVs are weak with corresponding F-statistics less than 10.16 (Full results are available in Table S5 in the supplementary materials.)

We estimated several different model specifications to assess correlates among climate shocks, vulnerability, and resilience in Zambia. We estimated two model variants where each model includes all the climate shock variables with either seasonal rainfall or the 30-year average for seasonal rainfall. Figures 4 and 5 report selected average partial effects for correlates between climate shocks and vulnerability and resilience, respectively. Table S6 (in the supplementary materials) reports full results for the control function probit and Table S7 reports results for the regular probit. The right-hand side panels in Figures 4 and 5 include all the climate shock variables and seasonal rainfall, while the left panels include all climate shock variables with the 30-year average rainfall. To check for robustness, we report further results in the supplementary materials for alternative models where we separate CSA into its constituent components (minimum tillage, fertiliser, and
hybrid maize seed) (Tables S8 and S9). For all estimations, CSA interacts with all climate variables to assess whether using CSA mediates the effects of climate shock on vulnerability and resilience. We also include the residuals from the first stage in all the reported results. Significance of these residuals confirms statistical endogeneity. We keep the residuals whether they are statistically significant or not because these choice variables are endogenous by construction.

We find evidence that using CSA influences the effects of climate shocks and directly improves resilience (Figure 5 and Table S6). Using CSA in the 2019 survey year (which corresponds to the period when outcomes are measured) is associated with a 22-percentage point increase in the probability that a household is resilient (Figure 5 and Table S6). The MT

![Figure 3. Proportion of chronic, transient, and never poor rural households between 2012 and 2019 in Zambia. Notes: Own calculations from RALS (2012-2019).](image)

![Table 2. First stage results on the relevance of instrumental variables.](image)

![Figure 4. Selected effects of climate exposure on vulnerability among smallholders in Zambia with 30-year average rainfall (left panel) and seasonal rainfall (right panel). Notes: A confidence interval for a point estimate that lies on either side of the zero shows that the estimate is statistically significant.](image)
component of CSA seems to be the main driver of these results (Table S9). These findings are in line with expectations that adopting CSA practices might help enhance resilience. This finding corroborates those of Michler et al. (2019), who found that CSA helped farmers adapt to rainfall variability in Zimbabwe, those of Ngoma et al. (2016) who suggest that droughts increase the probability of farmers adopting MT in Zambia, and Zambia’s CSA investment plan which finds that CSA increases household welfare in the long term (World Bank, 2018). These results should not be understood to suggest that CSA is some kind of ‘magic bullet’. If carefully packaged, some CSA practices may have potential to raise resilience. In our case where CSA includes the use of MT, inorganic fertilizer, and hybrid seed, the use of MT seems to be the biggest factor in improving resilience (Table S9) even if we do not further investigate the causal chain. Prioritizing what works where and under what circumstances is key in scaling CSA. Zambia’s CSA investment plan identifies cereal-legume crop diversification, commercial horticulture, agroforestry and reducing post-harvest losses as some of the most promising CSAs in the country (World Bank, 2018).

We also found that current growing season rainfall is associated with increased vulnerability and reduced resilience. The long-term effect of rainfall (measured by 30-year average rainfall) is also associated with reduced resilience. These findings linking exposure to climate shocks to worsened vulnerability and reduced resilience, imply negative consequences on livelihoods. Our findings suggesting that higher current growing season rainfall increases the chances that a household will be vulnerable and reduces their resilience are in line with Alfani et al. (2019) and Al Mamun et al. (2018), who found that El-Niño weather events reduced productivity and increased poverty in Zambia. Our findings are also in line with Azzarri and Signorelli (2020), who found that flood shocks increase poverty and reduce expenditures among households in SSA. These findings imply that poverty, expenditure, vulnerability, and resilience are linked. Our findings are also in line with Thurlow et al. (2012) and Ngoma et al. (2021), who found that climate change is likely to reduce agricultural productivity and worsen poverty and household welfare in Zambia. These results are also in line with findings in the Zambian Climate Smart Investment Plan, which suggests that climate change is likely to reduce crop productivity by up to 25% (World Bank, 2018).

The contrasting effects of long-term and current seasonal rainfall show the differences between enduring and short-term negative effects. While we do not measure how long-term rainfall might affect vulnerability and resilience directly, the paper, we can speculate that rainfall alters farmer behaviour. As suggested in Sesmero et al. (2018) and Mulenga et al. (2017), past weather events may influence farmers’ expectations of future weather patterns. These expectations in turn might influence current production decisions, including the choice of seed varieties and farming technologies.

The other results in Table S6, S8, and S9 (in the supplementary materials) are as expected. Having assets and higher education level of the household head are associated with reduced vulnerability and increased resilience. Female-headed households and those headed by older heads are associated with higher vulnerability and reduced resilience. The finding that assets and education enhance resilience are in line with Sesmero et al. (2018). These factors also reduce vulnerability. Our results suggesting that the gender of the household head affects household vulnerability and resilience in Zambia bring to the fore the gendered effects of climate shocks: female-headed households and adult-female only households are significantly more likely to be vulnerable and less resilient. These findings are in line with Umar (2021) who suggests that female-headed households are most vulnerable and least resilient. One reason this could be the case is because female-headed households do not always have access to similarly productive resources and land as do males (FAQ, 2011). This inequitable access to productive resources, coupled with the heavier societal burdens of home chores, likely worsens women’s vulnerability, and reduces their resilience.
We urge some caution in interpreting the results of this paper. First, while we attempted to address some key endogenous factors and their effects on vulnerability and resilience – namely, CSA adoption, crop diversity, and access to credit – the success of our approaches depends on how good the instruments used are, and how well the exclusion restrictions are met. These are difficult empirical issues and ones that every economist will question. Collapsing RALS data to cross sectional data that allows us to measure vulnerability and resilience after three-waves reduces our ability to take advantage of the panel structure of the data. We are, however, confident that our approaches – which allow us to better measure vulnerability and resilience and apply instrumental variable probit models – add value to existing studies linking climate shocks, CSA, vulnerability, and resilience.

Second, we acknowledge that CSA as defined in this paper (minimum tillage, inorganic fertilizer, and hybrid seed) captures only short-term effects. This is because we are not able to assess for how long farmers have used these CSA practices on the same plots. We propose that future research should control for long-term plot-level CSA effects on vulnerability and resilience.

Lastly, although our income-based poverty measures are presumably broadly aligned with consumption expenditure-based measures, they may be an imperfect substitute for expenditure-based metrics, which are more commonly used in the country.

6. Conclusion

The frequency and intensity of climate and weather shocks are increasing in Southern Africa, pushing rural households – especially smallholder farmers – into poverty. Understanding the extent of the problem and best-bet solutions in different contexts requires in-depth studies. This paper assessed the extent to which smallholder farmers in Zambia are exposed to climate shocks using both exogenous and self-reported shock measures. It then evaluated the impacts of climate shocks on vulnerability and household resilience and assessed the extent to which climate-smart agriculture (CSA) practices – defined as minimum tillage, inorganic fertilizers, and hybrid maize seed – influence outcomes. We used household data obtained from the nationally representative Rural Agricultural Livelihoods Survey (RALS). Vulnerability and resilience are defined based on whether a household is ‘poor’, ‘never poor’, ‘escaped poverty’, or ‘fell into poverty’ over the three-survey waves and measured in the third wave in 2019. As such, our measures of vulnerability and resilience give a longer time horizon beyond single year snapshots. We restricted our analysis to a subset of households re-interviewed over the three-waves for a total sample of about 6,531 households and applied an instrumented probit regression that allows us to control for endogeneity of some choice variables.

We found that smallholder farmers in Zambia are more exposed and therefore vulnerable to droughts, the more prevalent climate shock faced by rural households. Floods are an important risk in some years. The extent of exposure differs both spatially and over time, but on balance, Zambia’s Southern and Western Provinces are most exposed to climate shocks. About three-quarters of all smallholders are vulnerable and nearly one-quarter are resilient nationally. There are important differences between Provinces, with the Eastern, Muchinga, Northern, and North-western Provinces being the most vulnerable. Our multivariate analysis suggests significant correlation between (i) climate shocks and worsened vulnerability, and (ii) between climate shocks and reduced resilience. We also found some evidence suggesting that assets and education reduce vulnerability and increase resilience among smallholder farmers in Zambia, and that female-headed households are more vulnerable and less resilient. Using CSA is associated with increased chances that a household will be resilient in the short-term.

We therefore conclude that most smallholder farmers in Zambia are exposed to climate shocks and are vulnerable, and that climate shocks are associated with increased vulnerability and reduced resilience. The current use of CSA is associated with improved resilience among smallholder farmers. We draw two main implications from these findings. First, based on the positive association between CSA and resilience, there is need to invest in CSA research and development to scale out and scale up context-specific CSA practices. In the context of CSA as adaptation options, this implies a need for timely delivery of climate information services, through innovative digital platforms.

Second, given the significance of climate shocks on resilience and vulnerability, there is a need for more investments in risk mitigation strategies, such as weather indexed insurance and targeted social cash transfers and how to make these work effectively for smallholder farmers. This will enable farmers to access coverage against climate shocks and in turn help to reduce household vulnerability and increase their resilience. While there have been attempts to implement insurance programmes in Zambia, it is not clear if they have been successful or how to make such programmes work for smallholders. Other important complementary elements include facilitating asset accumulation and education that can increase resilience.

Notes

1. The paper by Thurlow et al. (2012) imposes changes in climate in 2025 on economic outcomes over the period 2006 – 2016.
2. These are years during which total rainfall during the growing season is between 405mm and 499mm.
3. The comparative rate of poverty in urban areas is 23.4 percent.
4. According to the Zambia data portal https://zambia.opendataforafrica.org/figgqzd/zambia-atlas-fact-dataset-4 (February 2013), the average population density in Zambia by 2015 was 20.16 persons per km². It was higher in Eastern and Southern Provinces at 34 and 21 persons per km², respectively.
5. From which the national poverty rate is derived.
6. At the time of writing, the 2015 LCMS is the data set that provides the most recent estimate of national, urban/rural, and provincial poverty rates in Zambia.
7. El Niño is an abnormal weather pattern which affects Zambia through increased drought severity, resulting in adverse effects on agricultural production.
8. This section draws heavily from a background report: Ngoma et al. (2019). Poverty and weather shocks: a panel data analysis of structural and stochastic poverty in Zambia. Available at http://www.iapri.org.zm/images/WorkingPapers/wp150_for_pdf_poverty_final.pdf.
9. Average ZMW/USD exchange rate at the time was 7.5.
10. In terms of poverty transitions, vulnerable households are those who are chronically poor, or those who fell into poverty by the third survey wave regardless of whether they were poor or not in the first and second survey waves. This includes households that were poor in the first and third waves but not in the second wave, those poor in the second and third waves but not in the first wave or indeed those that were not poor in the first and second waves but fell into poverty in the third wave.
11. This includes households that were never poor across the three survey waves, those poor in the first and second waves but not in the third wave, or poor in the first wave but not in the second and third waves, or ones that were not poor in the first and third waves but were poor in the second wave.
12. We constructed this measure based on personal communications with agronomists based at the Zambia Agricultural Research Institute (ZARI).
13. Computed as the Simpson index based on area cultivated per crop relative to total area cultivated.
14. MT is defined as the use of either ripping, planting basins, or zero tillage as the main tillage method at the plot level. Minimum tillage is the most prevalent form and the basic CSA principle in Zambia. MT practices are known to help farmers adapt to water stress by improving water collection and retention in planting stations, while hybrid maize seed and inorganic fertilizers are key in helping farmers build resilience.
15. In econometrics, “endogeneity” broadly refers to situations in which an explanatory variable is correlated with the error term.
16. Corresponding F-values for IVs are 4.6, 146 and 9 in Models 1, 2, and 3, respectively.

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Notes on contributors
Hambulo Ngoma is an Agricultural Economist at the International Maize and Wheat Improvement Center (CIMMYT) based at the Southern Africa Regional Office in Harare, Zimbabwe. His current work spans agricultural technology adoption, agricultural transformation, impact assessment, scaling, policy analysis, resilience, climate adaptation and mitigation and welfare analysis mainly focused on Malawi, Tanzania, Zambia and Zimbabwe. He holds a PhD in Applied Economics from the School of Economics and Business, Norwegian University of Life Sciences.

Arden Finn is a Senior Economist in the World Bank’s Poverty and Equity Global Practice. His current work focus is on the intersection of wellbeing and the Palestinian economy, and he also works on issues of economic mobility, the measurement of welfare and geographical targeting. Prior to joining the West Bank and Gaza team he worked primarily on South Sudan, Ethiopia and Zambia. He holds a PhD in Economics from the University of Cape Town.

Mulukab Kabis is an environmental scientist and researcher with a background in Ecology and Biological Sciences. Her current research focuses on the use of futures thinking methods for African-led transformative change in biodiversity and climate governance. Kabisa’s main research interests are scenarios development, biodiversity and climate policy analysis, and rural agricultural livelihoods. She is a PhD candidate at the Global Change Institute - University of the Witwatersrand.

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