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Relationship between poverty and climate: Does climate variability drive rural poverty in Zimbabwe?

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Abstract

Zimbabwe has set poverty reduction targets in a changing climate, yet the implications of climate variability for poverty remain under-explored. Utilising household datasets to explore the association between poverty, cereal productivity and climate variability indicators, we observe a negative association between prevalence of poverty and variability of precipitation, despite evidence of lower cereal productivity in districts with higher precipitation variability. Semi-arid districts have higher precipitation variability and lower cereal productivity, but lower poverty prevalence than wetter districts. Agriculture-reliant districts are poorer than those relying on non-agriculture livelihoods, such as employment and remittances. The results reflect that households in regions with long-lasting precipitation uncertainty may adapt better to climate change. Hence, poverty reduction interventions in a changing climate should not only be anchored in historical weather developments; the local context also matters. In heterogeneous regions, where people in some areas have adapted to addressing weather challenges, strategies to address climate challenges must be flexible. Policies that diversify agriculture-reliant rural economies will reduce the impacts of climate change on poverty. The results further demonstrate the importance of education and wage employment in poverty eradication. Hence, upscaling the education of farmers and creating employment are critical strategies for fighting poverty in a changing climate.

Key words: rural poverty, climate change, weather fluctuations, income source diversification, Zimbabwe

1. Introduction

Zimbabwe, like many other countries, has set targets for poverty reduction, recognising that future climate change may create challenges to reaching these targets. Effective policy for poverty reduction requires knowledge about how climate change will affect the rural poor, yet this relationship has not been explored adequately. Koubi (2019) argues that climate change will increase inequality across countries, thereby threatening the achievement of poverty- and inequality-reduction targets (sustainable development goals (SDG) 1 and 10). On the one hand, the increasing extreme weather events and precipitation variability due to climate change pose serious risks for the poor by destroying household assets, affecting health and education, increasing health shocks, degrading infrastructure, and causing general price increases (Narloch & Bangalore 2018). On the other hand, net producing households that have adapted to a changing climate may benefit from increased commodity prices (Dumortier *et al*. 2021), which may lift them out of poverty.

While governments set goals for poverty reduction in line with the 2030 Agenda for sustainable development, little is known in many largely agrarian countries, including Zimbabwe, about how weather fluctuations relate to poverty and its reduction. Effective strategies to address sustainable development goal 1 (SDG 1) and the African Union's Agenda 2063 – of ending poverty – require prior information on the implications of climate change risks for poverty, particularly for rural households. The impact of climate change on rural poverty will depend on how people respond to climate change-induced extreme weather events, particularly droughts in the case of Zimbabwe. Information on the relationship between poverty, precipitation variability and climate change is crucial to inform policy. Nevertheless, such information is not available to policy makers in Zimbabwe, despite numerous episodes of devastating droughts and floods.

The poverty rate continues to increase in Zimbabwe. Extreme poverty, which was only 22.5% in 2011/2012, rose from 30% (29.3% using the pre-update basket of goods) in 2017 to 38% in 2019 (Zimstat and World Bank 2019). In agricultural regions, such as Mashonaland West and Mashonaland Central, the proportion of households living under the poverty datum line (US$1.90 per day) is above 75% (Zimstat 2024). Over the past decades, extreme weather events such as droughts and floods have been increasing in these agricultural regions with high poverty rates (Mupepi *et al*. 2024). In 2024, the country experienced an extreme El Nino-induced drought and six million people required humanitarian assistance (OCHA 2024).

Despite harmony in many studies on the economic and social costs of climate change, and rising interest in the estimation of these costs, estimates have largely been framed in terms of aggregate impacts such as global or country-level impacts (Barbier & Hochard 2018; Hallegatte *et al*. 2018; Chapagain *et al*. 2020). Nevertheless, capturing the full impact of climate change on people's well-being, including the possibility of adaptation to it, requires a micro-level analysis (Justino 2009). Notwithstanding numerous studies on poverty carried out at the micro-level in Zimbabwe (Kinsey *et al*. 1998; Hoddinott 2006; Manjengwa *et al*. 2012; Pindiriri *et al*. 2015; Stoeffler *et al*. 2015), little has been done to examine the association between poverty and precipitation variability. Some of these studies include climate-related factors, but they have largely been based on single-point cross-sectional data and, in some cases, used weather fluctuations as being synonymous with climate change. For instance, Kinsey *et al*. (1998) and Hoddinott (2006) apply single-point cross-sectional data and identify climate change as one of the shocks driving poverty in rural communities. Climate change, however, is a dynamic phenomenon associated with long-term shifts in weather patterns

(Hallegatte *et al*. 2016). Furthermore, these micro-studies have mostly been based on a case study of a small area, such as a ward or a district with homogeneous weather and climate conditions and economic activities (Kinsey *et al*. 1998; Hoddinott 2006; Pindiriri *et al*. 2015). To account for heterogeneity across space and economic dependence, there is a need for wider coverage of localities with varying conditions of weather, climate and economic dependence.

Most previous poverty studies only focused on the one-sided effect that climate change and its associated extreme weather conditions make poor people more vulnerable and thereby increase the prevalence of poverty in areas susceptible to a high frequencies of drought (Bird & Shepherd 2003; Ahmed *et al*. 2009; Barbier & Hochard 2018; Hallegatte *et al*. 2018). However, there is evidence of lower poverty in some areas with higher average rainfall. For instance, the prevalence of rural poverty in Zimbabwe was 61% and 61.5% in regions III and IV, respectively, while it was 56.1% in the drier region V (Zimstat 2017).

The objectives of this paper are to assess the dynamics of the prevalence of rural poverty and precipitation and temperature at a sub-national level; examine the association between poverty, cereal productivity and precipitation variability; and analyse the implications of this association for the poverty–climate change relationship. Addressing these objectives will help policy makers understand the implications of climate change and increased variability in precipitation on poverty and cereal productivity. It may also help identify areas facing higher climate risks and requiring specific strategies for poverty eradication. The better targeting of anti-poverty programmes requires a good understanding of who the poor are, where they are concentrated the most, where they are deprived, and the extent of their vulnerability and exposure to weather shocks. Such an understanding is particularly relevant where there is strong political will to increase investments in social protection and social security, build resilience in smallholder agriculture, and realign public spending on agricultural development to effectively fight poverty (Ngoma *et al*. 2019).

The next section provides a brief review of the poverty and climate change literature. Section 3 describes the methods and the data. Section 4 presents and discusses the findings. Finally, Section 5 summarises the study and discusses policy implications.

2. Background: Climate change and rural poverty

Theory conceptualises poverty as a product of individual deficiencies, cultural conditions, economic, social and political distortions, geographical disparities, and cumulative and cyclical interdependencies (Bradshaw 2007). Climate change exacerbates geographical disparities in two ways. Firstly, disparities may grow when some households are exposed to an increased frequency of climate change-induced extreme weather events while others are not. Under such circumstances, cross-sectional surveys can be used to evaluate the impact of the increased frequency of extreme weather events on poverty only if the two groups are spatially separated. Secondly, a changing climate may create disparities for the same individual over time due to factors associated with vulnerability (Hallegatte *et al*. 2016; Barbier & Hochard 2018).

Previous findings on the impact of climate change on poverty in various countries show different paths through which climate change influences poverty (Ahmed *et al*. 2009; Bezgrebelna *et al*. 2024; Chaudhry 2024). Although the relationship between climate change and poverty is complex, one pathway is through agricultural productivity, labour productivity and food availability (Behrer *et al*. 2021; Ahmed *et al*. 2009) while the others are on welfare (Chaudhry, 2024; Ahmed et al., 2011) and learning (Jisung et al., 2020). For instance, Ivanic and Martin (2014) established that extreme poverty among consumers could increase by about 25% in countries such as Guatemala, India, Indonesia, Pakistan, Sri Lanka, Tajikistan and Yemen when climate change pushes prices up by 100%. In addition, the World Bank (2010) argues that, despite an improvement in poverty reduction experienced by countries, climate change is likely to reduce agricultural productivity in many tropical areas (Fuglie 2021). As conditions vary within countries, development paths of entire regions might diverge.

Furthermore, climate change influences poverty through its impact on assets (Baulch 2011). Over time, people build assets and exit poverty, while others experience the destruction or deterioration of assets and enter the poverty cycle (Baulch 2011). Climate-induced extreme weather events destroy people's assets and affect their health and education, and increase health shocks (such as death and illness) (Baulch 2011). Increased incidences of climate shocks, such as droughts and floods in agrarian sub-Sahara African countries, have led to crop failure and increased outbreaks of pests and livestock diseases, which in turn worsen poverty (Ngoma *et al*. 2019). Long-term droughts may also drive households to diversify their income-generating activities away from agriculture – dynamics are important.

There is a rich empirical literature on poverty and drivers of poverty in Zimbabwe (Kinsey *et al*. 1998; Hoddinott 2006; Manjengwa *et al*. 2012; Pindiriri *et al*. 2015; Stoeffler *et al*. 2015; Diwakar *et al*. 2018; Frischen *et al*. 2020; Oxford Poverty and Human Development Initiative [OPHI] 2020). These studies also identify climate change-related variables as drivers of rural poverty in agricultural communities. Frischen *et al*. (2020) further established that drought vulnerability and exposure vary substantially among Zimbabwean districts. Districts in the south-western provinces of Matabeleland North and South show particularly high exposure and vulnerability. According to the report on the Poverty Income Consumption and Expenditure Survey (Zimstat 2017), poverty is much higher in rural Zimbabwe.

A major drawback of these studies is that they rely largely on a static survey that accounts for household-specific heterogeneity, but fails to account for period-specific heterogeneity, as can be done by using repeated cross-sections or panel data. Both poverty (Hallegatte *et al*. 2016) and climate change (Frischen *et al*. 2020) are dynamic processes that cannot be captured fully using one-point cross-sectional data. It is against this background that the current study closes this literature gap by making use of repeated cross-sectional data from existing poverty, incomes, consumption and expenditure surveys (PICES) (2011 and 2017) to assess the extent of climate change-related poverty in Zimbabwe. A major strength of repeated cross-sectional data is the ability to track sub-national poverty and climate change over time. While these datasets are not panels, which would allow control for unobserved factors, they have the advantage that they are very large, something that few panels can claim. The data were also collected with virtually identical survey instruments using the same sample frame.

In contrast to the literature showing negative impacts of climate change on agriculture (e.g. Molua *et al*. 2010), Hertel and Rosch (2010) argue that, for net producers, climate change-induced price increases may lead to higher returns from agriculture. Barbier and Hochard (2018) argue that, due to different intensities of climate-change disruptions across the world, impacts will range from negative to moderately positive. In countries where some sub-national districts are affected by climate change more than others, the impact of climate change will vary by region. Hence, this paper assists policy makers in targeting policy. Unlike previous work on poverty determinants in Zimbabwe, we examine how changes in an area's poverty are related to rainfall and temperature variability.

3. The empirical strategy and data

3.1 Empirical strategy

Zimstat has constructed several poverty profiles since the Riddell Commission of Inquiry into Incomes and Pricing in 1981, but there has been no formal effort to measure climate change-related poverty (Malaba 2006). We used the Zimstat PICES and data from the agricultural productivity module (APM) of PICES (Zimstat 2017) to explore the relationship between poverty, cereal productivity and climate change. A major weakness of cross-sectional datasets is that the same individuals are not followed over time. However, we made use of repeated cross-sections. The main advantage of using repeated cross-sections, which are representative of districts, is that we can account for both district-specific and period-specific heterogeneity. Both vary within and between repeated cross-sections. Furthermore, district-level variables can be constructed from the different PICES and followed over time. With representative district samples of the PICES datasets, individual and household-level data can be collapsed to the district level. This supports the data on climate change indicators which, is only available at the district level.

We applied two national-level cross-sectional datasets (PICES) (2011 and 2012) because Zimbabwe does not have longitudinal data for household surveys (different households are interviewed in each round of the PICES). The 60 districts had over 32 000 households altogether; one of the real advantages of the PICES is that it is representative at the district level. We generated district-level variables from several households in each district, e.g. the percentage of poor households, average farm size in each district, percentage of women in each district, water access (%), electricity access, etc.

As in previous poverty measurement studies in Zimbabwe, we focused on monetary poverty (see Zimstat 2017). Although a unidimensional measure is considered incomplete, as people face multiple deprivations such as education, health and living standards, among others (Alkire & Foster 2011), monetary poverty remains a useful poverty measure because it captures a household’s ability to meet critical basic needs (Atamanov *et al*. 2020). However, we complement it with other deprivations, such as education, assets, employment and living standards (OPHI 2020; Stoeffler *et al*. 2015).

The empirical strategy involves three stages. First, we constructed district-level measures of rural poverty, cereal productivity and household characteristics using the 2011 and 2017 PICES. Variables representing monetary and other forms of deprivations were constructed for each district. Climate change indicators, such as precipitation intensity and temperature, are mostly uniform for households in the same locality. Hence, for a reasonable variability in climate variables among sampling units, and given that Zimbabwean districts have not changed significantly since the 2011 PICES, districts are an appropriate aggregation. With fixed district boundaries, estimates can be followed over time, providing district-level estimates. Second, we constructed a longitudinal dataset for climate-related variables. The main problem with PICES data is the missing climate variables, such as precipitation and temperature. However, district-level data on these variables were obtained from the Meteorological Services Department. Precipitation and temperature variability for each district were measured and applied as indicators of climate change. Each variable was collapsed to the district level using district averages. Third, we estimated the association between each form of deprivation and climate change indicators. The measurement of association between poverty prevalence, cereal productivity and climate change indicators was done in two ways.

Simple measures of association were computed using scatterplot correlations, differences in means and correlations from a simple ordinary least squares (OLS) method, presented as:

$$p_i = C_i'\varphi + Z_i'\theta + e_i, \quad (1)$$

where p_i is the poverty-dependent variable measured as the proportion of the poor in district i, which takes various forms of deprivation indicators (monetary, education, health and assets) or a measure of cereal productivity. C is a vector of climate variability indicators (precipitation variability and temperature changes), which includes averages over 60 years, Z is a vector of control variables that includes district characteristics such as education, agroecological characteristics, and the proportion of labour force population in wage employment. These serve as a proxy for employment creation, proportion of women in the district, agricultural role and other district-level factors, and e_i is the error term, where $e_i \sim N(0, \sigma^2)$. For the cereal productivity model, Z includes inputs in production measured as in the APM. In Equation (1), the variation in variables is across districts. Hence, we ran two separate regressions using a single cross-section in each case: 2011 PICES first, and then the 2017 PICES. By using the two PICES separately, we can check the consistency and reliability of the associations. With reliable measures of associations, we expected to see the same pattern of relationship between climate indicators and poverty measures using both the 2017 and the 2011 datasets. For the productivity model, only the APM in the 2017 PICES (Zimstat 2017) was applied (the only year for which the APM was available). The vector of parameters, φ, provides a good estimate of the correlation between climate indicators and poverty when using a single cross-section. Other estimated forms of district-level deprivations include the percentage of adult population deprived of education, employment, water, electricity and assets.

Equation 1 accounts for district heterogeneity, but not for period heterogeneity, so we also estimated a dynamic measure of association between weather indicators and poverty prevalence in districts. As in Equation (1), these results must be interpreted with caution, as causal effects cannot be measured perfectly. We estimated a simple regression using first differences between the 2011 and 2017 PICES to supplement scatterplots and difference in means. Equation 2 was estimated using two PICES (2011 and 2017) concurrently. Significant differences may exist over time within the same district, or across districts. For instance, some districts experienced a more than 1% rise in maximum temperature between 2010 and 2017. Similarly, average precipitation declined in some districts, while it increased in others. As such, we estimated the following model using OLS:

$$\Delta p_i = \Delta C_i'\gamma + \Delta Z_i'\vartheta + u_i, \quad (2)$$

where $\Delta p_i = p_i^{2017} - p_i^{2011}$ is the change in the prevalence of poverty in district i between 2011 and 2017, $\Delta C_i = C_i^{17} - C_i^{11}$ is the change in climate indicators over the two periods in which the two PICES were done (2011 and 2017), ΔZ_i is the change in control variables, γ and ϑ are simple dynamic association parameters, and u_i is the error term assumed to be well behaved. The parameter γ measures the association between weather indicators and monetary deprivation.

3.2 Measurement of variables and data

Monetary poverty and consumption per capita were the only measures of deprivation applied in the regressions, while other deprivations, such as education, electricity and water access, were only applied in the correlations. Cereal productivity, as measured by yield per hectare, was also used as the dependent variable in the productivity model. Table 1 presents the measures of poverty (p), cereal productivity and other forms of deprivations applied in this paper. The change in poverty (Δp) in Equation (2) is the difference between the 2017 and 2011 monetary poverty.

Table 1: Poverty measures

Poverty measure	Definition and measurement
Monetary poverty	A household is monetarily poor if it does not have adequate financial resources to provide its members with basic goods and services necessary for their survival. We applied the widely used monthly extreme/food poverty line estimated by Zimstat at US$29.8 per person. Poverty, the main dependent variable in the regressions, was measured as the proportion of poor rural population in a district.
Consumption per capita	The district-level mean of the value of consumption per person. This is the same variable that was compared to the poverty lines to compute poverty.
Cereal productivity	Measured using yield per acre of the main staple food cereal, maize.
Education deprivation	An adult of at least 18 years of age is education deprived if he/she has never attended secondary education. It is the proportion of deprived adult population in a district.
Water access deprivation	Measured as the proportion of people without access to clean water in a district.
Electricity access deprivation	Measured as the proportion of people without access to electricity.
Asset deprivation	A household is deprived if it does not own at least two of the following assets or a car: television, fridge, radio, home theatre, bicycle, computer, cell phone, microwave and stove, tractor, irrigation equipment, harrow, plough, land and livestock. The proportion of asset-deprived adult persons was estimated at district level.

Note: Only monetary poverty, productivity and consumption were used in both regressions.

The main regressors, which are climate indicators, include drought risk or precipitation variability, temperature variation and growth (Table 2).

Table 2: Climate indicators

Climate indicator	Definition and measurement
Normal precipitation	Normal precipitation is when precipitation falls within ± 25% of the long-term average as defined in Zimbabwe's National Drought Plan (Environmental Management Agency [EMA] 2019). In this paper, we applied a 60-year average.
Precipitation variability	Measured as the number of years each district experienced precipitation below normal, divided by the number of years of the study period (60 years). Also measured using the coefficient of variation.
Temperature variation	Measured using the coefficient of variation.
Drought frequency	This is the frequency of droughts within a district over 60 years.
Change in precipitation	This is the 2017 value less the 2011 value.
Change in temperature	Measured the same way as the change in precipitation.

Unlike the national definition of drought as a condition of annual precipitation being less than 75% of 500 mm per annum, which is uniform for heterogeneous districts, we defined drought as a condition of annual precipitation less than 75% of the district's 60-year mean precipitation. District i, with a 60-year mean annual precipitation of $\bar{R}_i^{60yr}$ computed as $\frac{\sum_{t=1}^{60} R_{it}}{60}$, and annual precipitation of R_{it} at time t, is in drought if it is at least 25% below the mean; that is, if:

$$R_{it} < 0.75\bar{R}_i^{60yr} \tag{3}$$

The number of years for which Equation (3) holds, divided by 60, provides a measure of precipitation variability/drought risk for district i, used as a poverty correlate in Equation (1).

There were 60 administrative districts in the 2011 PICES and 62 in the 2017 PICES. The 2017 PICES divided some districts into two, but the datasets allow us to follow the same districts from 2011 to 2017. In addition to poverty and climate indicators, as in Tables 1 and 2, poverty correlates used in this paper include district wage employment status, share of women, education, agriculture dependency, remittance dependency and a dummy variable for southern districts.

3.3 Stylised facts of climate and poverty indicators

3.3.1 Climate indicators

Table 3 reports the means and variations of district-level climate change indicators. The district with the largest variation in rainfall had a coefficient of variation (CV) of 0.41, while the one with the smallest had a CV of 0.19. The most stable indicator of climate change in rural Zimbabwe was the maximum temperature, of which the CV was only 0.08, while precipitation variability was the most unstable, with a CV of 0.34.

Table 3: Descriptive statistics of climate change indicators in 60 rural districts over 60 years (from 1960)

Variable	Obs.	Mean	St. dev.	Min	Max	CV
Annual precipitation (mm)	60	720.4	166.7	333.6	1458.3	0.23
Annual maximum temperature (°C)	60	26.8	2.1	20.5	30.8	0.08
Number of droughts over 60 years	60	11.2	3.7	4	20	0.33
Precipitation variability over 60 years	60	0.19	0.07	0.07	0.35	0.34
Rainfall variation over 60 years (sd. Dev.)	60	201.4	40.9	135.9	389.6	0.20
Rainfall variation over 60 years (CV)	60	0.29	0.05	0.19	0.41	0.16

Notes: The estimates are averages of 60 rural districts over 60 years; CV = coefficient of variation.
Source: MSD (2024)

Precipitation variability is negatively associated with mean annual precipitation (see Figure 1). Variability was highest in the arid districts of Masvingo, Matabeleland and part of the Midlands, and lowest in the Mashonaland and Manicaland districts. For instance, districts in Masvingo and Matabeleland, such as Chiredzi, Mberengwa, Mwenezi, Beitbridge, Gwanda, Bubi and Tsholotsho, experienced at least three droughts every 10 years. Districts such as Hurungwe and Guruve, in Mashonaland, experienced only one drought in 10 years. Precipitation was more variable in the semi-arid southern region than in the northern region. Southern districts (with red dots in Figure 1) can therefore be considered to have worse climatic conditions than the northern districts, which justifies the use of a dummy variable to delineate the southern region as a high drought-risk region.

Mean precipitation has declined in Zimbabwe, an indication of the increasing frequency of drought because of a changing climate. For instance, in Chimanimani and Chipinge, mean precipitation declined by at least 10% between 2010 and 2017. Maximum temperatures grew by at least 1% in Gokwe South, Nkayi, Murehwa, Chimanimani, Bindura, Nyanga and Shamva. Only a few districts, such as Gwanda, Zaka, Matobo, Gweru, Umguza, Umzingwane, Insiza, Bubi and Shurugwi, experienced a decline in mean maximum temperature over the decade. However, for most districts, the change in mean maximum temperature in the last decade compared to the previous decade is less than one percentage point. The coefficients of variation show that maximum temperatures are partially stable in all districts.

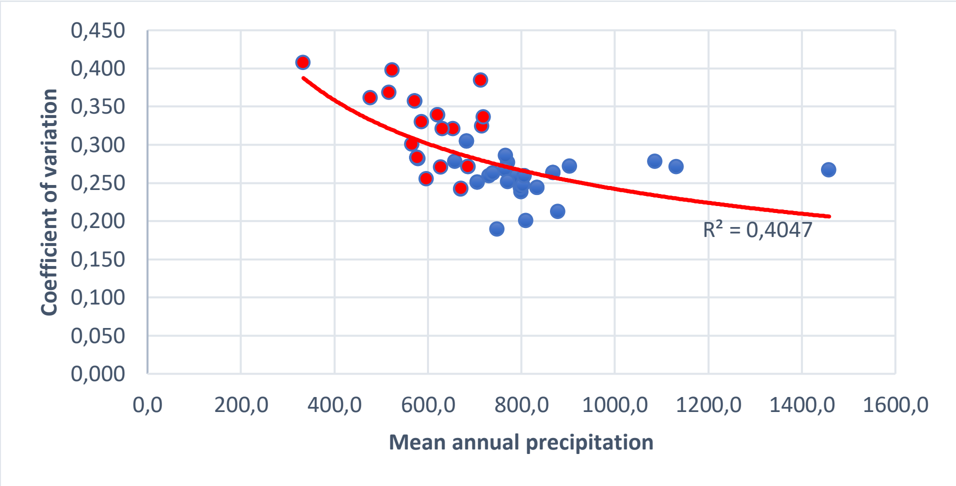


Figure 1: District-level precipitation levels and variability (1960 to 2019)
Source: Authors' illustration

3.3.2 Poverty measures

The descriptive statistics of monetary deprivation and other forms of deprivation for 60 rural districts are presented in Table 4. On average, extreme poverty increased substantially between 2011 and 2017, while real consumption fell by nearly 17 percentage points.

Table 4: District descriptive statistics of poverty measures

Variable	Obs	Mean	Std. dev.	Min	Max
Proportion of people in extreme poverty in 2017	60	0.32	0.12	0.11	0.65
Proportion of people in extreme poverty in 2011	60	0.21	0.11	0.03	0.61
Real per capita consumption in 2017 (US$)	60	58.1	11.6	35.1	78.3
Real per capita consumption in 2011 (US$)	60	75.6	20.2	34.2	140.5
Number of home assets or gadgets in 2017	60	2.1	0.41	1.4	3.6
Number of agricultural assets in 2017	60	3.5	0.86	0.67	5.3
Proportion of households with access to water in 2017	60	0.84	0.08	0.66	0.98
Proportion of households with access to electricity in 2017	60	0.43	0.15	0.05	0.87
Proportion of adults with at least secondary education in 2017	60	0.65	0.10	0.45	0.85
Proportion of adults with wage employment in 2017	60	0.09	0.05	0.03	0.27

Notes: Consumption in 2017 was deflated using 2011 as base year; the poverty measures were derived using real consumption expenditures per capital. Other variables were only analysed for 2017.

In 2017, the highest prevalence of extreme poverty was found in districts in the Mashonaland provinces. Surprisingly, extreme poverty in 2017 was lower in districts located in the semi-arid southern districts with the highest rainfall variability and lower cereal productivity compared to the northern districts (Table 5). In addition to a lower prevalence of poverty, the semi-arid southern districts showed a greater reduction in rural poverty between 2011 and 2017 compared to the northern districts, despite lower cereal productivity. This reflects adaptation and the diversification of income sources, and an understanding of what is behind this impressive reduction in poverty is crucial for policy makers.

Table 5: Summary statistics for outcome variables for rural areas in the Southern and Northern districts

Characteristic (mean)	Southern districts (n = 26)	Northern districts (n = 34)	Total (N = 60)	Difference	t-statistic
Extreme poverty in 2011	0.219	0.208	0.212	0.011	0.362
Extreme poverty in 2017	0.267	0.358	0.320	-0.091***	-2.998
2011 per capita consumption	74.8	76.2	75.6	-1.41	-0.263
2017 per capita consumption	62.3	55.0	58.1	7.30***	2.496
Precipitation variability	0.230	0.163	0.192	0.07***	4.460
Mean maximum temperature	27.84	26.12	26.8	1.72***	3.486
Cereal productivity (mt/ha)	0.59	1.73	1.15	-1.14***	2.835

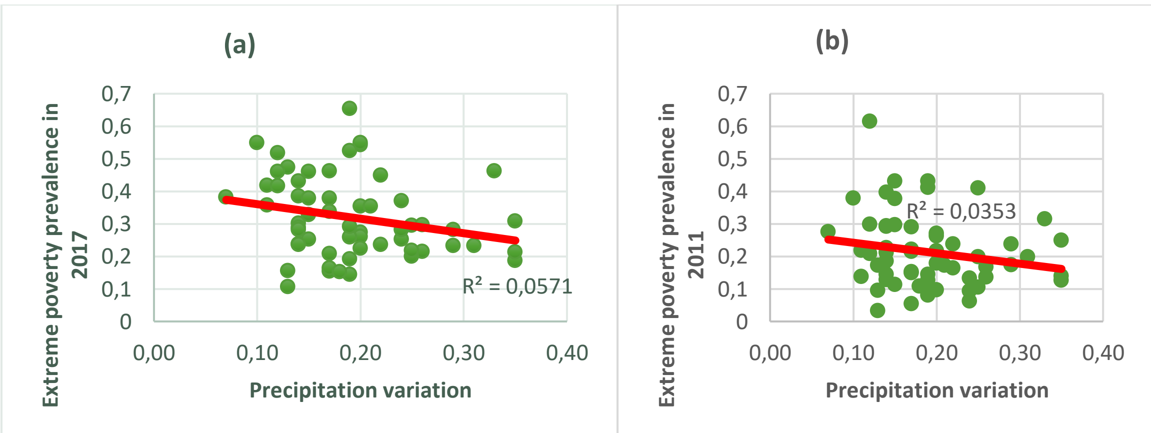
Notes: ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Poverty measures are mean district proportion of poor; precipitation variability is the probability of a drought; and consumption is measured in US$. Cereal productivity is proxied using maize yield per hectare, since maize is the main cereal crop in the country.

4. Findings

The nature of district-level climate change indicators and their association with monetary poverty, cereal productivity and other deprivations is explored in this section. First, we present the association between climate change indicators and poverty measures. Second, we present climate change indicators and other control factors as correlates of poverty.

4.1 Association between poverty and climate change indicators

The scatterplots in Figures 2(a), (b) and (c) demonstrate a negative association between the prevalence of rural poverty and the variability of precipitation. Despite having lower cereal productivity, as in Figure 2(d), districts with more variable precipitation have lower poverty prevalence than those with lower variability in precipitation. This result holds for both the 2017 and 2011 datasets. Getting the same finding from two different datasets provides some degree of confidence regarding the reliability and robustness of the findings. The 2017 PICES reinforces these findings by showing that poverty prevalence is highest in agroecological regions IV, III and I, which are not as dry as region V. In 2017, 43%, 42%, 40% and 38% of the people in regions IV, I, III and II, respectively were extremely poor, while only 36% of those in the driest region, V, were extremely poor.



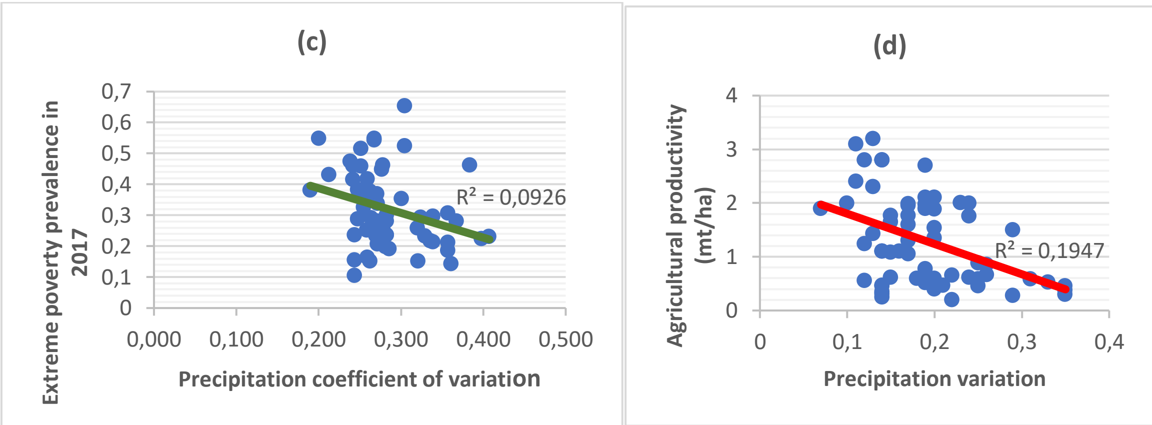


Figure 2: Rural poverty prevalence by district, cereal productivity and precipitation variability

Source: Authors' illustration

Districts in the southern part of the country have more variable maximum temperatures (Table 5) but lower poverty prevalence than those in the northern areas. A negative association is evident between variability of maximum temperature and extreme poverty prevalence (Figure 3(a)). Semi-arid districts in southern Zimbabwe are characterised by more variable temperatures than districts in the north, yet have a lower poverty prevalence. Figure 3(b) demonstrates a negative association between temperatures and the proportion of population who have at least completed primary education in a district. This is consistent with the findings by Jisung *et al*. (2020), namely that high temperatures negatively affect learning, but this could also be a result of educated people migrating from these areas.

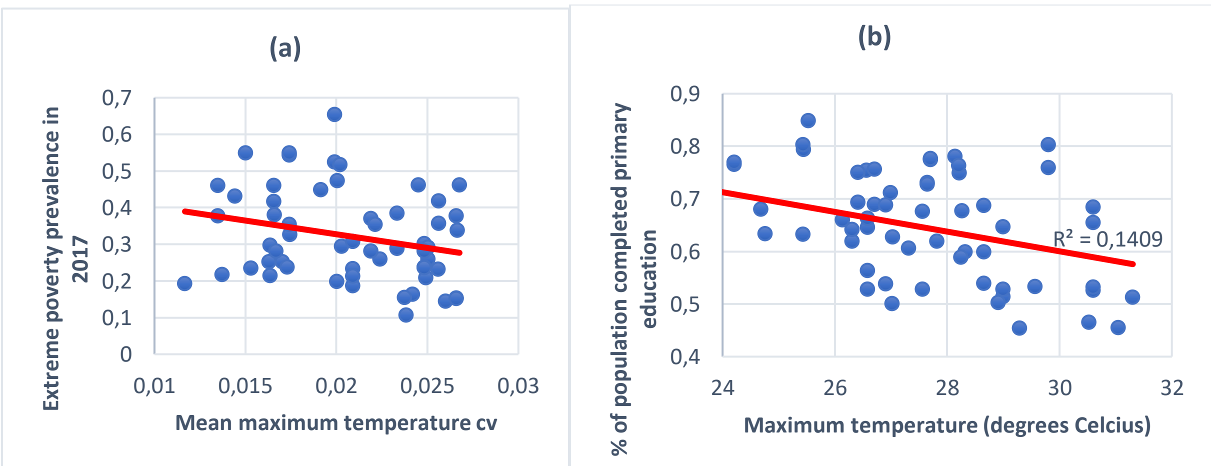


Figure 3: Rural poverty prevalence by district and its association with education and temperature variability

Source: Authors' illustration

Furthermore, we evaluated increases in temperature and precipitation over the period 2004 to 2011 and 2011 to 2017, and correlated the changes in these climate indicators with the prevalence of poverty (Table 6). Mean maximum temperatures have increased by 0.89 percentage points more in the northern districts compared to the southern districts. Although poverty prevalence declined in both the southern and northern districts, the decrease was significantly larger in the semi-arid southern districts. The prevalence of extreme poverty increased by 37.5 percentage points more in the northern districts, where temperatures have increased more than in the southern districts over the past two decades. The findings must be treated with caution, however, because of the short time span considered, which cannot fairly address climate change.

Table 6: Mean differences in indicator growth from 2004 to 2017 between the southern and northern districts

Characteristic (mean)	Southern districts (n = 26)	Northern districts (n = 34)	Total (N = 60)	Difference	t-statistic
Temperature growth	0.81	1.71	1.33	-0.89**	2.32
Precipitation growth	-6.86	-3.69	-5.03	-3.16	1.21
Extreme poverty growth	56.93	94.46	78.56	-37.53**	1.68

Note: ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

4.2 Other forms of deprivation, remittances, and differences in income sources

The difference by district classification of other forms of deprivation in 2017 is presented in Table 7. In terms of household assets, the results show no difference in asset ownership. For agricultural assets, a household in the southern districts owned an average of 0.7 assets more than the average in the northern districts, largely driven by differences in livestock ownership. In addition to a lower prevalence of monetary poverty, southern districts had more assets and better access to water and electricity, but were not better in education.

Table 7: Differences between southern and northern rural districts in other forms of deprivation in 2017

Characteristic (Mean)	Southern districts (n = 26)	Northern districts (n = 34)	Total (N = 60)	Difference	t-statistic
Access to water (% of population)	85.4	82.2	83.5	3.2*	1.60
Access to electricity (%)	48.2	39.4	43.1	8.8**	2.28
Home assets (household mean)	2.1	2.1	2.1	0.1	0.64
Agricultural assets (household mean)	3.9	3.2	3.5	0.7***	3.34
Education (% of adult population)	62.2	66.7	64.7	-4.4**	-1.68
Foreign remittances (% recipients)	4.52	1.35	2.69	3.17***	4.14
Domestic remittances (% recipients)	15.31	10.97	12.81	4.34*	1.57

Note: ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively

Rural households in southern Zimbabwe are major recipients of foreign and domestic remittances. These households are 3.2 percentage points more likely to receive foreign remittances compared to those in the northern districts. The ten districts with the largest share of recipients of foreign remittances were all from the southern part of the country, except for Chegutu. Districts bordering South Africa and Botswana were among the top recipients of foreign remittances. Households receiving foreign remittances tend to be better off than households receiving domestic remittances in situations with a weak and unstable domestic currency.

Although the main source of income of people in both the northern and southern rural districts was agriculture, there were significant differences between the two. A larger percentage of households in the southern districts derive their livelihood mainly from remittances, while a larger percentage in the northern districts derive their income mainly from agriculture. Figure 4(a) demonstrates that poverty prevalence is higher in districts with a larger population relying on agricultural income. In contrast, the prevalence of poverty is negatively associated with reliance on remittances (Figure 4(b)).

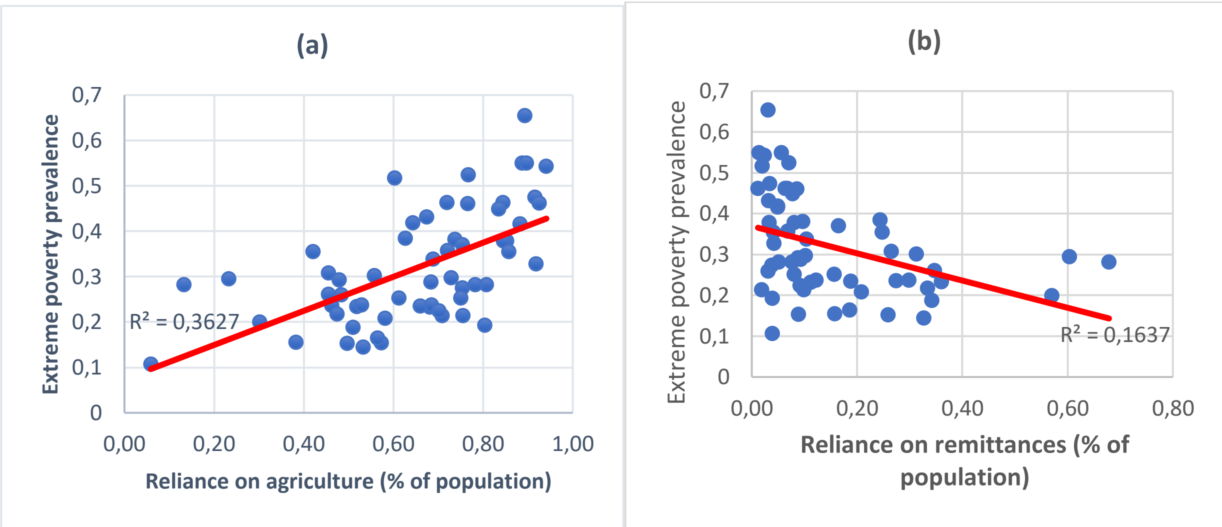


Figure 4: Poverty and reliance on agriculture and remittances
Source: Authors' illustration

4.3 Climate-related drivers of poverty

Table 8 presents results from six simple regression models for measuring correlations between climate change indicators, cereal productivity and poverty. Using the log of consumption per capita as the dependent variable provides similar conclusions. The findings are consistent with the descriptive results explained in the previous sections. For instance, precipitation variability is negatively associated with poverty prevalence, irrespective of the model applied (models 1 and 4 in Table 8). Model (6) further supports a higher per capita consumption in the semi-arid southern districts, as demonstrated by the statistically significant positive coefficient of the location dummy. Districts that experienced a larger growth rate in precipitation during the previous decade were associated with higher poverty (Model 3). However, there is no evidence to support the relationship between mean maximum temperatures and prevalence of poverty. Nevertheless, the results confirm previous findings by the World Bank (2010) that precipitation variability reduces cereal productivity in developing countries (Model 5 in Table 8).

District-level rural poverty was positively associated with reliance on agriculture (Model 1), but negatively associated with reliance on remittances (Model 4). The southern districts, which rely on remittances more than the northern districts, had a lower prevalence of poverty, while the northern districts, which rely more on agriculture, had a higher prevalence of poverty. Other factors associated with poverty prevalence include education and employment. Poverty prevalence is negatively associated with education and wage employment. Similar findings are revealed in Model (6), which regresses the log of consumption per capita on climate change indicators and other controls. Higher consumption is associated with higher variability in precipitation, higher education, residence in the southern districts and a lower reliance on agriculture.

The main conclusion is that districts with higher variability in precipitation have lower cereal productivity and, surprisingly, a lower prevalence of poverty than those with less variable precipitation, all other factors being controlled for. Reliance on agriculture is larger in the northern districts, while reliance on remittances is larger in the semi-arid southern districts. Non-agricultural activities, such as wage employment and education, play a significant role in poverty eradication in both the northern and semi-arid southern districts.

Table 8: Simple regression of the correlation between climate and poverty indicators

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
VARIABLES	**Poverty 2017**	**Poverty 2017**	**Poverty growth 2004 to 2017**	**Poverty 2017**	**Cereal productivity 2017**	**Log(pccons) 2017**
Precipitation variability	-0.526***			-0.441**	-0.068***	0.858**
	(0.186)			(0.203)	(0.025)	(0.406)
Education	-0.307**	-0.453***		-0.467***	0.102**	0.529**
	(0.115)	(0.113)		(0.126)	(0.057)	(0.265)
Wage employment	-0.0421	-0.020		-0.666***		0.008
	(0.264)	(0.257)		(0.244)		(0.611)
Agriculture	0.311***	0.313***				-0.475***
	(0.0691)	(0.068)				(0.146)
Gender (share of women)	0.792	0.007		0.0479		
	(0.745)	(0.704)		(0.808)		
Drought frequency		-0.239***			-0.110***	
		(0.065)			(0.048)	
Fertiliser application					0.033***	
					(0.012)	
Precipitation growth			1.928*			
			(1.135)			
Max temperature growth			0.284			
			(7.455)			
Remittances				-0.346***		
				(0.0858)		
Southern districts					-1.14***	0.123*
					(0.450)	(0.066)
Farm size (ha)					0.105*	
					(0.070)	
Farm size squared					-0.015**	
					(0.07)	
Constant	0.279	0.454	87.9***	0.794*	0.624***	3.912***
	(0.406)	(0.394)	(15.53)	(0.428)	(0.019)	(0.657)
Observations	60	60	60	60	60	60
R-squared	0.492	0.571	0.049	0.460	0.514	0.402

Notes: Standard errors in parentheses; *** = p < 0.01, ** = p < 0.05, * = p < 0.1

Unlike previous findings (Bukari & Aluko 2023), this study reveals that, despite reducing productivity in agriculture, high temperatures and reduced precipitation might not always imply high poverty levels. These findings suggest the importance of poverty reprogramming in Zimbabwe, where humanitarian aid has largely been skewed to the dry regions of the country.

5. Discussion, conclusion and policy implications

Variability in precipitation was greater in the semi-arid regions, and districts with higher mean annual precipitation had less precipitation variability. Despite having lower cereal productivity and fewer adults who have completed primary education, semi-arid districts with higher precipitation variability had lower poverty. The results suggest that, although precipitation variability reduces cereal productivity, it does not always translate into impoverishment. Since climate change is expected to increase temperatures and precipitation variability, the results reflect a crucial policy implication that governments should not only target regions known to have long-lasting precipitation and temperature variability, but also agriculture-reliant regions without long-lasting precipitation and temperature variability. In some of the former areas, people have adapted to addressing weather challenges. Effective targeting therefore should also include those regions with low precipitation variability, where people may lack knowledge and experience of adaptation.

The main implication is that climate change is likely to increase the prevalence of poverty in districts that rely on cereal production (in particular maize) in the short run. But, in the long run, communities experiencing persistent droughts adapt to these extreme weather events through learning process. They diversify into high-value non-agricultural activities such as migration, mining and drought-resilient agricultural activities like livestock production. Climate change will therefore have detrimental consequences for poverty eradication if interventions continue to be informed by the historical climate conditions of regions, which may continue to promote the flow of resources to communities well adapted to extreme weather events, while missing the agriculture-dependent communities in areas with low variability in precipitation. The other implication is that the underlying problems are forcing people to migrate to neighbouring countries in search of income. This may not be a sustainable strategy for long-term poverty reduction. Any disturbance in remittance inflows may significantly modify poverty, making home-based strategies a better option.

Diversification from primary cereal production to higher-value non-agricultural activities may significantly reduce the negative impacts of climate change on poverty. Government policies in Zimbabwe have largely been biased towards the promotion of agriculture. But this has not been effective in reducing poverty, and the situation may worsen due to a changing climate. Local employment creation through upscaling the growth point concept, agro-processing and industrialisation through local value addition can diversify income sources and improve incomes in these localities. Government support in agriculture can be effective in reducing poverty in a changing climate if it targets high-value agricultural production such as cattle ranching, which thrives in semi-arid regions and hence is suitable in a changing climate. The issue is, “diversify to prevent climate change impacts or wait for climate-induced poverty to force you to diversify”.

In addition to pinpointing the importance of accounting for climate variability in policy programming on poverty, the study adds to the sparse literature on the relationship between poverty and climate variability. Future studies should consider undertaking experiments to measure the causal effect of a changing climate on poverty. The availability of longitudinal household surveys in the future may help improve these findings.

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