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The effect of local climatic conditions on household consumption: a case study of South Africa

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The article explores the causal effect of local climate conditions on household consumption in South Africa. The climatic conditions are represented by monthly average temperature and precipitation. The study utilises the nationally representative 2017 National Income Dynamics Study (NIDS), wave 5 data and 2017 Climate Research Unit (CRU) climate data. The parsimonious quantile regression shows that climatic conditions (precipitation, temperature, wet days, and cloud cover) impact household per capita consumption. The quadratic quantile regression model analysis shows that household per capita consumption is convex in precipitation. Below the turning point, increased precipitation is associated with decreased household per capita consumption. Above the turning point, increased precipitation is related to increased household per capita consumption. Regions that receive very low precipitation or experience extreme temperatures (very cold or very hot) require tailor-made interventions to alleviate consumption. When we control for household characteristics, the impact of climatic conditions on household per capita consumption is weak. Providing inclusive development policies and programmes can mitigate the impact of climatic conditions on household per capita consumption.

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Introduction

Climatic losses and damages have regularly occurred worldwide and in South Africa. Researchers concur that adverse climatic conditions affect people differently depending on their socioeconomic status, but the effect is more pronounced in poverty-stricken individuals (Barua et al. 2014). Adverse climatic conditions can, therefore, affect the consumption patterns of households. The size of a consumption budget is a good indicator of whether a household is poor or non-poor (Hallegatte and Rozenberg, 2017). Climate conditions can influence production positively or negatively, affecting consumption streams. Favourable climatic conditions stimulate production in weather-dependent industries, whereas unfavourable conditions restrain production in climate-dependent sectors (Liu and Long, 2023; Reza and Sabau, 2022). If production is constrained due to adverse climate change effects, it can influence consumption more severely especially in countries with wide inequality and high poverty levels.

Evidence shows that extreme climatic conditions harm the poverty-stricken more than the non-poor (Leichenko and Silva, 2014). The poor lack resources to mitigate the hazardous impact of climatic conditions such as droughts, hurricanes, extreme temperatures and floods on their welfare and have limited knowledge to counteract the effect of climate. The poor are more likely to live in regions with harsh weather conditions where they are more likely to eke a living out of climate-sensitive activities such as agriculture (Angelsen and Dokken, 2018). They are more likely to survive on low-income informal jobs and less likely to hold insurance to protect them from adverse climatic conditions (Barua et al. 2014; Brainard et al. 2009). Situations faced by individuals living in varied climatic environments can determine their consumption and assets holding ability. South Africa is one of the most unequal countries in the world, with over 55 percent of the population living in poverty (World Bank, 2018). The prevalence of poverty in South Africa is multidimensional, shaped by historical political circumstances, social, individual characteristics and behaviour, psychological, economic, and environmental factors. While accepting the multi-dimensional nature of poverty in South Africa, a few scientific research has focused on the effect of climatic conditions on household consumption, which can be an indicator of welfare.

A growing body of literature considering the determinants of household poverty has probed the impact on family size, dependency ratio, gender, education, employment status, income, occupation, age, landholding and livestock herd, infrastructure—electricity, proximity to market centres and residing in rural areas on household poverty, measured by income or consumption (Garza-Rodriguez et al. 2021; Heshmati et al. 2019; Lekobane and Seleka, 2016; Peng et al. 2019a; Teka et al. 2022). However, the link between household consumption and local climate conditions has only received little attention, particularly in Africa and non-Western, Educated, Industrialized, Rich and Democratic countries (non-WEIRD). Most of the studies on the effects of climate variability (change) have focused attention on the link between climate variability (change) and a broad set of economic outcomes, among them non-agriculture wages (Oliveira et al. 2021), agricultural labour supply (Antonelli et al. 2021), income (Deryugina et al. 2014), earnings (Isen et al. 2017), economic growth (Dell et al. 2012; Zhao et al. 2018; Zivin and Neidell 2014), agricultural production (Burke and Emerick, 2016; Schlenker et al. 2006) and income inequality (Diffenbaugh and Burke, 2019).

This study examines the relationship between household consumption (measured by household per capita consumption) and local climate conditions (defined as regional variability in temperature and precipitation) in South Africa. Precipitation patterns and temperature in South Africa vary from place to place, suggesting that climatic conditions can affect the welfare of people differently by their spatial location. Household consumption patterns are an essential indicator of household poverty (Garza-Rodriguez, 2018). Poor households tend to have constraint consumption streams compared to wealthy counterparts. The study utilises the nationally representative 2017 National Income Dynamics Study (NIDS), wave 5 data collected and validated by Southern Africa Labour and Development Research Unit (SALDRU) at the University of Cape Town and the 2017 Climate Research Unit (CRU) climate data from the University of Anglia. Acknowledging that poverty is a multifaceted problem with various causes, we estimate various multivariate cross-section regression models that control for confounding factors (individual characteristics) that influence household poverty and consumption. These models enable us to pick the true heterogeneous effects of local climate conditions (context where individuals live) on household consumption differentiated by regions.

South Africa presents a unique and exciting opportunity to study the effect of local climate conditions on household poverty and brings three contributions to existing literature. Firstly, since the advent of democracy in 1994, South Africa has implemented several measures to mitigate poverty, unemployment, and inequality, such as Black Economic Empowerment, social grants, housing, education, and public health policies. These measures have been identified in various policy documents, starting with the Reconstruction and Development Programme (RDP), which was the first prescription of the post-apartheid era to the current National Development Plan: Vision 2030 (NDP). While the measures have led to widespread economic and social welfare improvements, South Africa's poverty, inequality and unemployment levels are among the highest in the world (World Bank, 2018).

The persistence of these problems, more than three decades after the end of apartheid, suggests that the implemented policy interventions have been ineffective in achieving their set objectives. As a result, South Africa might fail to meet the Sustainable Development Goals (SDGs) 1, Target 1.1, of eradicating extreme poverty by 2030 (see United Nations, 2022). Thus, to effectively address poverty in the country, all determinants of poverty must be investigated. Accordingly, in addition to conventional determinants of household poverty, the study becomes unique by investigating the effect of climatic conditions.

Secondly, while several studies have examined the determinants of household poverty in South Africa, these studies have focused attention mainly on the effects of traditional household factors. Among them, employment status, level of education, geographical location, race, and gender, among others (Lindiwe Makhalima, 2020; Maloma, 2016; Mdluli and Dunga, 2021; Posel and Rogan, 2012; Serumaga-Zake and Naudé, 2002; Woolard and Klasen, 2005). However, to the best of our knowledge, we are unaware of a study examining the link between local climate conditions and household consumption in South Africa. The few existing studies examine the impact of climate variability/change on the economic well-being of female-headed households (Flatø et al. 2017), economic productivity and labour availability (Shayegh et al. 2021) and income inequality (Dasgupta et al. 2020).[1] This study adds to this research by empirically examining the effect of local climate conditions on household consumption in South Africa.

Thirdly, the spatial geography of South Africa shows that different places within the country have varying climate conditions ranging from flooding and very cold temperatures to droughts and extremely high temperatures. Established evidence shows that economic outcomes (among them wages and unemployment) also vary significantly across regions in South Africa (Kwenda et al. 2021; Mudiriza and Edwards, 2021). Given that the effect of climatic conditions is entangled with multi-dimensional poverty, regional-specific factors such as climate conditions, which also vary substantially across geographical locations, are potential explanatory factors of household poverty in South Africa. Thus, controlling for regional heterogeneity provides evidence from a new perspective in the South African context.

Given these contributions, the study provides a better and deeper understanding of the determinants of household poverty in South Africa, which is currently dominated by household factors. Accordingly, the study contributes towards the practical policy debate on household consumption in South Africa. The goal of alleviating poverty could benefit from policies that are well-informed about the determinants of household consumption.

The rest of the paper is structured as follows. Section 2, provides the literature review Section 3, describes the Data, and Section 4 presents the methodology. Section 5 presents and discusses the empirical results, while section 6 concludes the study.

Literature review

The theory of determinants of poverty. Absolute or relative deprivation is an indicator of poverty. The absolute approach explains poverty as when citizens cannot afford to acquire basic human needs such as food and shelter, among others (Allen, 2017). The relative approach views poverty as the minimum acceptable standard of living a person achieves compared to other citizens (Peng et al. 2019a, 2019b). Three different approaches have been used to explain the determinants of poverty, namely, micro or individual level, contextual or neighbourhood level and macro or structural level (Bradshaw, 2007; Garza-Rodriguez et al. 2021). A micro-level approach to poverty analysis is when individual characteristics and behaviour explain deprivation. The contextual level approach to poverty analysis posits that neighbourhood-level factors can propagate poverty, and for this study, climatic conditions can be a typical example. Lastly, economic, social, and political factors that give people limited opportunities constitute structural causes of poverty (Bradshaw, 2007; Garza-Rodriguez et al. 2021; Peng et al. 2019a, 2019b). Poverty affects individual and household consumption. High levels of poverty tend to constrain consumption. Micro, contextual, and structural determinants of poverty can influence individual and household consumption. This study focuses mainly on the contextual and micro-level approaches to causes of poverty while acknowledging the multi-dimensional nature of poverty. A unidimensional method that uses the monetary approach to measure poverty is applied in this study (Alkire et al. 2011).

Empirical literature on the causes of poverty. Several studies used a wide range of theoretical poverty perspectives to investigate the determinants of poverty, focusing mainly on demographic variables (for example, gender, age, race, household size), human capital characteristics (for example, level of education, employment status), Stressful life events, (for example, loss of employment, divorce) and contextual or neighbourhood characteristics (for example, climatic conditions, climate change, geographical location) among others (Garza-Rodriguez et al. 2021; Peng et al. 2019a, 2019b).

Demographic characteristics. Several studies investigating the determinants of poverty have used a wide range of individual demographic characteristics such as gender, age, race, and household size, among others. The conclusion reached by several studies shows that female subjects are more likely to be poor compared to their male counterparts (Chen et al. 2019; Ravindra and Minuwanthi, 2020). These findings were also confirmed in South Africa, where females are more likely to be in poverty than males (Biyase, 2005). Therefore, the hypothesis is that females are more likely to be relatively impoverished with poor consumption patterns than males. The point is that females are more likely to hold less education, be less likely to be employed in high-paying jobs, more likely to have children care responsibilities and suffer from feminisation poverty (Pearce, 1978).

Following the life-cycle hypothesis, the incomes of individuals are higher during working years and are lower before entering the job market as well as after retirement. Studies concluded a U-shaped relationship between poverty and age squared of the household head (Lekobane and Seleka, 2017). Some studies found an inverse relationship between age of the household head and poverty (Iqbal et al. 2020; Sekhampu, 2013).

Political, social, psychological, economic, and historical factors that have deprived races of opportunities are also significant determinants of poverty. Studies have confirmed that some races or ethnic groups are more likely to be poor when compared to others (Ravindra and Minuwanthi, 2020). According to Francis and Webster (2019), 4.1% of white South Africans are classified as poor compared to 20.5% of Indians, 56.8% of coloureds and 70.75% of black South Africans.

Other demographic characteristics associated with poverty are household size, dependence ratio (those that belong to non-working age groups) and the number of children under 6 years, among others. Large households are usually associated with high poverty and their consumption is constrained due to low per capita consumption or income. A huge dependency ratio reduces the per capita income and household consumption. Young children require more attention, leading to families hiring maids, or one of the parents would have to forego employment to take care of young ones. A high number of dependents constrains the income of households and is positively associated with poverty (Lekobane and Seleka, 2017; Ogutu and Qaim, 2019; Ravindra and Minuwanthi, 2020).

Human capital characteristics. The level of education, usually measured by the number of years of education, is a human capital characteristic associated with earning a better salary. People who earn high salaries tend to have better consumption streams. Another human capital characteristic that has been used in several studies is employment status. Unemployed people, who have constrained consumption and sources of income, are more likely to be poor. Studies have confirmed an inverse relationship between poverty and the number of years in education (Garza-Rodriguez et al. 2021; Lekobane and Seleka, 2017). Similar conclusions were arrived at in a South African study (Biyase, 2005).

Contextual or neighbourhood approach. The impact of climatic conditions on poverty can be explored in the spirit of the contextual neighbourhood approach. Evidence shows that the context in which one survives determines one's poverty situation. Some of the neighbourhood approach variables used in the previous studies are geographical location and climatic conditions (Garza-Rodriguez et al. 2021). Some studies confirm that people living in rural areas are more likely to be poor when compared to those living in urban centres (Biyase and Zwane, 2018; Ravindra and Minuwanthi, 2020). Urban centres are usually well-serviced and have better facilities that ensure improved human development and consumption patterns. Climatic conditions affect individuals who survive on climate-sensitive activities, affecting their consumption patterns. Individuals working in the agriculture sector or being self-employed were found to be more likely to be in poverty (Barua et al. 2014; Leichenko and Silva, 2014). Adverse climatic conditions negatively affect goods production, leading to poor consumption and poor livelihoods (Hallegatte and Rozenberg, 2017).

Schlenker et al. (2006) find that an increase in temperature leads to a decrease in agricultural output across counties in the United States, while Hsiang (2010) finds that positive temperature shocks negatively affect income in Caribbean-basin countries. Dell et al. (2012) find that higher temperatures not only lead to a reduction in income levels but also substantially reduce economic growth in poor and rich countries. In another research, Graff Zivin and Neidell (2014) find evidence of a nonlinear relationship between economic growth and temperature using county-level data for the United States. Their results showed that temperature increases at the higher end of the distribution reduce labour productivity in industries with high exposure to weather shocks. Similarly, Zhao et al. (2018) also find evidence of a nonlinear association between temperature and subnational economic growth using global subnational data. Their findings showed that at colder temperatures, an increase in temperature increases economic growth, but beyond an overage of 16 °C, an increase in temperature decreases economic growth. The nonlinear relationship was also confirmed for Uganda by Antonelli et al. (2021), who found that agricultural labour supply was optimised at an optimal temperature of 16 °C and for the United States by Deryugina et al. (2014), who found that personal income per capita is concave in temperature, with a maximum at about 15 °C.

Of the few available studies to examine the relationship between climate variability/change and household poverty, Narloch and Bangalore (2018) explored the link between household poverty and environmental risk factors in Vietnam. They found that temperature and precipitation, among other factors, affect household expenditure. Similarly, Aggarwal (2021) explored the relationship between climate shocks and household poverty in India and found that temperature positively affects household consumption. In another study, Azzarri and Signorelli (2020) examined the link between climate conditions and household poverty across Sub-Saharan African countries. They found that flood shock positively influences household poverty, while temperature and humidity negatively affect it. Constrained consumption caused by climate change can result in malnutrition, disease prevalence and stunted growth. These challenges have far-reaching outcomes that can potentially affect the welfare of the poor and communities. A study on COVID-19 concluded that the return to poverty differs by region and the characteristics of the individual (Ge et al. 2022). The study by Ge et al. (2022) confirms the spatial nature of poverty and how it can vary from region to region. In this study, we hypothesise that varying climatic conditions in South African regions impact household consumption.

Studies have investigated the impact of climate on macroeconomic determinants of poverty using aggregated values of production (gross domestic product) and expenditure (Škare and Družeta, 2016). Although increasing GDP and achieving economic growth are known to reduce poverty, they can fail to address the income distribution goal (Dollar and Kraay, 2002). Using aggregated GDP values to explain climate change's impact on poor individuals can be inappropriate. Income and expenditure shares of poor people in the national income are too low to capture the effects of climate change on their welfare. If the consumption of poor households is constrained, the change in their consumption due to climate will have little impact on the national income (Hallegatte and Rozenberg, 2017). Using microeconomic-level datasets such as households can go a long way in investigating the effect of climate on the poor and the rich.

While these studies clearly show that climate conditions influence household poverty, the results are mixed and inconclusive. Accordingly, there is a need for more research in this area, as understanding the relationship between household consumption and local climate conditions is fundamental for assessing household well-being, especially in Africa, where many households rely heavily on agriculture for their food security and livelihoods. Yet, they have inadequate managing capacities for controlling or coping with extreme climate conditions (Chersich and Wright, 2019).

The impact of area-specific climatic conditions on household consumption. Area-specific climatic conditions can either positively or negatively impact household consumption. Favourable climatic conditions can boost household consumption, while adverse climatic conditions can drastically reduce consumption. Affordability and availability of consumption goods and services can depend on prevailing climatic conditions. Normal rainfall patterns boost agricultural production compared to excessive rainfall and drought conditions that hamper productivity and negatively impact consumption and incomes(Angelsen and Dokken, 2018; Hallegatte and Rozenberg, 2017). Adverse climatic conditions such as abnormal temperature and rainfall can increase costs on food, loss of assets, increase insurance on damaged properties, higher energy demands, loss of jobs, failure to attain education, reduce water sources and poor health care, further constraining the consumption streams of individuals and households (Reza and Sabau, 2022). The main thrust of this study is to investigate the effect of local climatic conditions proxied by rainfall and temperature on household consumption expenditure in South Africa.

Data sources

The primary data source for this study is the nationally representative 2017 South African National Income Dynamic Study (NIDS), wave 5 data (Southern Africa Labour and Development Research Unit (SALDRU)), 2018. NIDS, wave 5 was administered to over 47,000 individuals in 13,700 households. However, for our study, we limit our sample to 7,135 households with complete information on all the relevant variables. NIDS wave 5, collected various socioeconomic variables at the individual and household levels central to our study. These include demographic characteristics (age, gender, and race), income, consumption, education level, assets, household debt, and employment status.

In addition, we use geospatial climate data, mainly temperature and precipitation, produced by the Climate Research Unit (CRU) at the University of East Anglia (https://www.uea.ac.uk/web/groups-and-centres/climatic-research-unit/data)(Harris et al. 2020). The climate data combines data from >4000 weather stations worldwide and satellite data to estimate monthly(yearly) average climate data from 1901–2020. The advantage of this database is that it is provided at fine spatial resolution (0.5×0.5 degree) grids, which allows us to extract the climate data for different geographical levels. We aggregate the data to 52 districts following the geographical boundaries used in the 2011 Census, which matches the district boundaries in the 2017 NIDS data. Finally, we merge the climate data for 2017 with 2017 NIDS wave 5 data based on the 52 districts in South Africa so that each household is assigned the average yearly climate data for its corresponding district.[2]

Measurements. Existing studies have used different variables as measures for household poverty, among them income, consumption, and a binary poverty status variable (Aggarwal, 2021; Azzarri and Signorelli, 2020; Garza-Rodriguez, 2018; Garza-

Rodriguez et al. 2021; Heshmati et al. 2019; Peng et al. 2019a, 2019b). This study uses household per capita consumption as our primary measure of household poverty. Household consumption is a better and more reliable measure of household poverty than household income because consumption is less vulnerable to under-reporting bias (Garza-Rodriguez et al. 2021). Hence, we choose to use household consumption. To compute the per capita consumption for a household, total consumption was divided by household size (number of individuals in the household). Poor consumption levels and patterns are indicative of poverty challenges. For robustness checks, we also capture household poverty using household per capita income[3], asset index, as well as a poverty status indicator based on Statistics South Africa's 2017 upper-bound poverty line[4], where a household is considered poor if the per capita monthly income of the household is less than 1138 Rands (Statistics South Africa, 2018).

As key independent variables, we include measures of local climate conditions, namely average monthly precipitation and temperature. In contrast, climate factors have widely been used to explain the variation in economic outcomes like wages, income inequality and economic growth (Antonelli et al. 2021; Diffenbaugh and Burke, 2019; Oliveira et al. 2021). However, these climate factors have rarely been used to explain household poverty. As shown in section 5 (Fig. 2), precipitation and temperature vary significantly across regions in South Africa, with some regions experiencing extreme drier and warmer weather conditions. The considerably extreme local climate conditions experienced in some regions of South Africa have led to severe droughts (Mahlalela et al. 2020), and these droughts are likely to affect household welfare, especially households who rely heavily on agriculture for their livelihoods.

Climatic conditions can constrain the production of goods and services that depend on climate outlook. Thus, we exploit the exogenous variation in temperature and precipitation that are random across regions to assess the effects of local climate conditions on household poverty. Existing studies also confirm evidence of a non-linear relationship between climate conditions and other economic outcomes like labour supply, economic growth, and income (Antonelli et al. 2021; Shayegh et al. 2021; Zivin and Neidell, 2014). Thus, we also include the second-degree polynomial terms of temperature and precipitation to capture the non-linear relationship between climate conditions and household poverty. We had other local climate variables for robustness checks, mainly vapour pressure, wet days, and potential evapotranspiration.

We further controlled for traditional household characteristics that influence household poverty. The empirical literature on household poverty determinants mainly guides the choice of the included household characteristics. Following existing literature, we included the age of the household head to capture work experience and the gender of the household head to capture possible labour market discrimination. Like in previous studies, we included the race of the household head to capture possible racial discrimination caused by apartheid-era policies. We also included the household dependency ratio to capture the potential effects of dependency on household resources. A high dependency ratio in a household reduces the available resources to each household member (Lekobane and Seleka, 2016). We incorporate a rural-urban dummy to capture location effects as consumption is likely to be higher in urban areas due to household proximity to better employment and economic opportunities, good infrastructure, and quality services (Serumaga-Zake and Naudé, 2002). In addition, we include the mean level of education of adults aged 15 years and above in the household to account for the effects of education. Education is a critical enabler for absorption in the labour market as it increases the chances of employment and employment in a stable and high-paying job.

We further control for employment status, having an employed adult increases the probability of high income and welfare in a household. Employment plays a vital role in household welfare as labour market income contributes the most significant share to total household income in South Africa (Gradín et al. 2021). We also include a dummy for children under 6 years in the household to account for household composition. Having a child under 6 years in the family is likely to affect household income because one of the household members, predominantly female, will have to reduce or stop participating in the labour market to provide caring responsibilities to the children, or someone will have to be hired to take care of the children. We included an infrastructure index of three household indicators (electricity, piped water, and flush toilet) to capture the effects of access to services. Wealthier households are more likely to access better household services than poorer households. We also included an asset index generated using principal component analysis showing the assets held by a household. Our analysis also included total household debt computed in the NIDS wave 5 collected in 2017. All the statistics are provided at the household level. The definitions of all the variables described above are given in Table 1.

Methodology

To empirically explore the effects of local climate conditions on household poverty, we used ordinary least squares (OLS) regression and quantile regression models. While the OLS regression model estimates the average response of the dependent variable to changes in the independent variables, the quantile regression model provides a range of estimates for different quartiles of the distribution of the dependent variable (Garza-Rodriguez et al. 2021). Thus, compared to OLS regression, which reveals constant estimates for the whole distribution, quantile regression allows for a more robust investigation and determination of asymmetric effects of specific covariates on the dependent variable (Zhang, 2017). As a result, the differential effects of specific covariates across the different quartiles of the dependent variable can be compared. Further, quantile regression is also a more robust estimation procedure when heterogeneity is markedly present in the dependent variable as specific covariates are allowed to vary over the whole range of the distribution of the dependent variable (Marrocu et al. 2015). In addition, quantile regression is a more robust estimation procedure when the errors are not independent and identically distributed, as it is more robust to non-normal errors and outliers. Thus, the quantile regression model is our preferred model, providing a more comprehensive statistical analysis opportunity than the traditional OLS regression model.

However, to interpret the quantile regression results, we contrasted them with the OLS regression, which was also estimated for comparing results by Garza-Rodriguez et al. (2021). Thus, as our benchmark model, we estimated the following parsimonious OLS regression model:

$$y_{hr} = \alpha + \beta T_r + \delta P_r + \varepsilon_{hr} \tag{1}$$

where, y_{hr} is the natural logarithm of current per capita consumption or natural logarithm of income per capita or asset index of household h in region r; T_r and P_r are the logarithm of annual average temperature and precipitation in region r and ε_{hr}, a random error term. α, β,and δ are a set of parameters to be estimated. We estimate Eq. (1) using the OLS regression model, which uses the minimisation of squared errors method to obtain the parameters. The key identifying assumption in estimating Eq. (1) is that spatial variation in temperature and precipitation is exogenous to household poverty. Our assumption is supported by

Table 1 Definitions of variables used in the study.

Variable	Definition
Dependent variables	
Per capita consumption	Total household consumption expenditure (the market value of all goods and services purchased by a household) in a month is divided by household size (the number of individuals in the household).
Per capita income	Total household income in a month is divided by household size (the number of individuals in the household).
Income poor	A binary outcome variable equals 1 if the household per capita monthly income is below the upper-bound poverty line of 1138 Rands in 2017 and 0 otherwise.
Household variables	
Age of head	Age of the head of household
Head is black	Household head is black/ African
Head is female	Household head is female
Mean education of adults	Mean level of education of adults aged 15 years and above in the household
Employed adult	Dummy variable equal to 1 if a household has at least 1 employed adult and 0 otherwise
Children under 6 years	Dummy variable equal to 1 if a household has at least 1 child under 6 years old and 0 otherwise
Dependency ratio	Number of dependents aged 0 to 14 years and over the age of 65 years divided by the total working-age population aged 15 to 64 years.
Rural area	Dummy variable equal to 1 if a household resides in rural areas and 0 otherwise
Household total debt	Calculated household total debt from household responses
Asset index	An index constructed using the principal component analysis consisting of durable assets owned by households
Homeland status	Ratio giving the proportion of the area of each district that fall in former homeland areas and the ratio ranges from 0 to 100%
Infrastructure index	An index constructed using the principal component analysis consisting of three household indicators—access to electricity, piped water and flush toilet.
Climate variables	
Temperature	Average yearly temperature measured in degrees Celsius (°C).
Precipitation	Average yearly Precipitation measured in millimeters (mm)
Vapour pressure	Average yearly vapour pressure measured in kilopascal (kPa)
Wet days	Average yearly wet days measured in millimeters (mm)
Potential evapotranspiration	Index of average yearly potential evapotranspiration that combines mean, maximum, and minimum temperature, vapour pressure and cloud cover.

existing studies that have used climate variables as sources of exogenous variation in explaining variation in income (Diffenbaugh and Burke, 2019). Thus, we are confident that the model will reveal the true effects of local climate conditions on household poverty without the need to determine causality. The standard errors are clustered at the district level to account for correlation and heteroskedasticity among households within a district.

However, to improve our understanding of the effects of local climate conditions on household poverty, we further estimate the effects of temperature and precipitation in different quantiles on household poverty using the quantile regression (QR) model. The QR helps us investigate how temperature and precipitation affect household per capita consumption across the distribution. The quantile regression model estimates the coefficients by minimising the estimation's weighted sum of absolute residuals (Fusco et al. 2023). The quantile regression model is expressed as follows (Aggarwal, 2021):

$$\min_{\in R, \beta \in R^k} \sum_{r=1}^{n} c_\tau \left(y_{hr} - \alpha - \beta T_r - \delta P_r \right), \text{where} c_\tau(k) = (\tau - 1 * [k<0])k \tag{2}$$

where τ is the quantile and $0<\tau<1$, for $r = 1, \ldots \ldots, n$. The intercept and slope coefficients, α, β, and δ differ by income quantile τ. We follow existing literature and estimate quantile regression equations for the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} quantiles (Marrocu et al. 2015). In estimating equation (2), the dependent and local climate condition variables are the same as those used in the OLS regression model.

Some studies have confirmed a non-linear relationship between climatic conditions and poverty indicators (Reza and Sabau, 2022). Certain levels of unfavourable climatic conditions can constrain household consumption, income and asset holding. To investigate whether there are optimal points at which climatic conditions impact household consumption, we estimated OLS quantile regression models with linear and quadratic variables of precipitation and temperature (Popoola et al. 2018). We simultaneously estimated OLs and Quantile regression to compare the effect of climatic conditions on the consumption per capita distribution. We estimated the following quantile regression.

$$\min_{\in R, \beta \in R^k} \sum_{r=1}^{n} c_\tau \left(y_{hr} - \alpha - \beta T_r - \vartheta T_r^2 - \delta P_r - \omega P_r^2 \right), \text{where} c_\tau(k) = (\tau - 1 * [k<0])k \tag{3}$$

Where T_r^2 and P_r^2 are quadratic variables of temperature and precipitation. We calculated the optimal point of the quadratic regression model. We further controlled for household factors, including age, gender, race, household debt, asset index, geographical location, household size, dependence ratio, and educational level of the head of the household.

Empirical results

This section presents and discusses our results. We aim first to establish whether a statistically significant relationship exists between household consumption and local climate conditions. To do so, we start by presenting background statistics of key variables. Then, we present restricted OLS and quantile regression models that include local climate conditions captured by average temperature and precipitation as the only factors influencing household poverty measured by household per capita consumption. We then extend the models to include additional household controls. Lastly, we also present results for some robustness checks using alternative measures of household poverty and local climate conditions. For all the models, household per capita consumption and local climate conditions are in log form, meaning that the estimates measure the percent change in

Table 2 Summary statistics of key variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: Household variable					
Per capita consumption	7 135	4283.423	9578.363	48.250	260734.00
Per capita income	7 135	5026.936	11752.240	100	867666.70
Income poor	7 135	0.314	0.464		
Age of head	7 135	41.874	13.783	14	100
Head is black	7 135	0.819	0.385		
Head is female	7 135	0.450	0.498		
Mean education level	7 135	10.484	2.764	0	18
At least one employed adult	7 135	0.800	0.400		
Children under 6 years	7 135	0.261	0.439		
Dependency ratio	7 135	0.462	0.705	0	7
Rural area	7 135	0.271	0.444		
Homeland status	7 135	0.178	0.237		
Household debt	7 135	130 120.20	10 341.61	5	17 200 000
Asset index	7 135	0.346	0.020	−5.733	3.515
Infrastructure index	7 135	0.463	1.157	−2.599	1.257
Panel B: Climate variables					
Temperature	52	18.519	1.857	8.84	27.130
Precipitation	52	45.912	19.670	0.033	242.45
Vapour pressure	52	13.571	2.764	9.475	20.852
Wet days	52	6.920	2.480	2.387	11.959
Potential evapotranspiration	52	3.849	0.472	3.022	5.060

Note: Panel A reports the summary statistics for key household variables for households with complete information, while Panel B reports the summary statistics of the climate variables aggregated to 52 district councils. Variable definitions are provided in Table 1.

household per capita consumption resulting from a percent change in a particular local climate condition.[5]

Background statistics. Table 2 presents summary statistics (simple household average, district average and the standard deviation) of key variables used in the empirical analysis for the effects of local climate conditions on household poverty in South Africa in 2017. The statistics show that of the 7135 households with complete information, the average household per capita consumption and income is about 4283 and 5027 rands per month, respectively. About 31.4% of the households are income poor and the average age of the household head is about 42 years. However, we have 18 child-headed households. While this is possible, this might be a data error because an analysis of the data shows that of the 18 households, 12 households have other household members who are 18 years and above.[6]

The statistics further show that 81.9% of the household heads are black or African, 45.0% are female, and the mean level of education of adults in the household aged 15 years and above is about 10.5 years. Further, 80.0% of the households have at least one employed adult, while 26.1% have at least one child under the age of 6 years. The dependency ratio of the households is about 46%, implying that close to half of the households have dependents. Most households reside in urban areas, as only 27.1% live in rural areas. The average household debt was R130 120.20 and the mean asset index was 0.346. The climate variables show that the average monthly temperature was 18.5 °C, while the average monthly precipitation was 45.9 millimetres. Overall, the minimum and maximum variables clearly show that the average values mask significant heterogeneity for household and climate variables.

To unmask this heterogeneity, Fig. 1 presents a map of the spatial distribution of household per capita consumption and income across regions in 2017. The lighter the colour, the lower household per capita consumption and income (implying higher poverty). The map indicates that household per capita consumption and income vary significantly across regions in South Africa. Households with relatively low per capita consumption and income are highly concentrated in former homeland areas (areas with blue tracing boundaries in Eastern Cape, KwaZulu-Natal, and Limpopo), implying high household poverty. Figure 2 presents a map of the spatial distribution of average yearly temperature and precipitation across regions in 2017. The darker the colour, the higher the average temperature and precipitation. The maps confirm spatial variation in temperature and precipitation across regions in South Africa. On average, temperatures are relatively high in former homeland areas in the country's northern parts and the coastal regions of KwaZulu-Natal. At the same time, precipitation is relatively high in the eastern former homeland areas of KwaZulu-Natal.

There appears to be a spatial coincidence between household poverty and climate conditions, as areas with low per capita consumption tend also to have high average temperatures and precipitation. In areas where there are adverse climatic conditions, a negative association between per capita consumption and local climate conditions is anticipated. This negative association is further confirmed in Table 1A in the Appendix, which shows a simple correlation between household welfare measures and climate variables used in our analysis.[7] Our estimation results in the next section will allow us to determine the true association between household poverty and climate conditions in South Africa.

Regression Results. The study investigated the parsimonious impact of climatic conditions on household per capita consumption, per capita income, asset holding and income-poor. Table 3 shows estimates from the OLS regression with climatic conditions as the only independent variables. There are four models in Table 3 showing results for per capita household consumption (1), per capita household income (2), asset index (3), and income-poor household (4). The results show that a 1% increase in temperature leads to a 0,244 significant decrease in household per capita consumption. Similar results are confirmed with precipitation, a 1% increase in rainfall leads to a 0.084 significant decrease in household per capita consumption. The direct linear relationship between climatic conditions and household

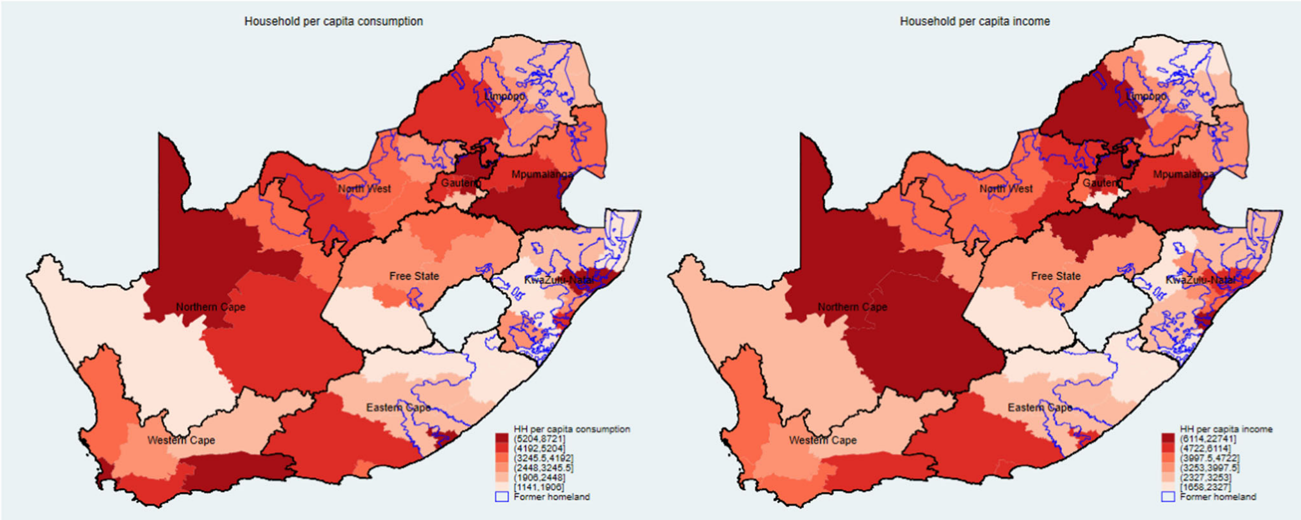

Fig. 1 Spatial distribution of household per capita consumption and income across districts in South Africa, 2017. Source: The authors' calculation based on weighted 2017 NIDS, wave 5 data aggregated to 52 districts.

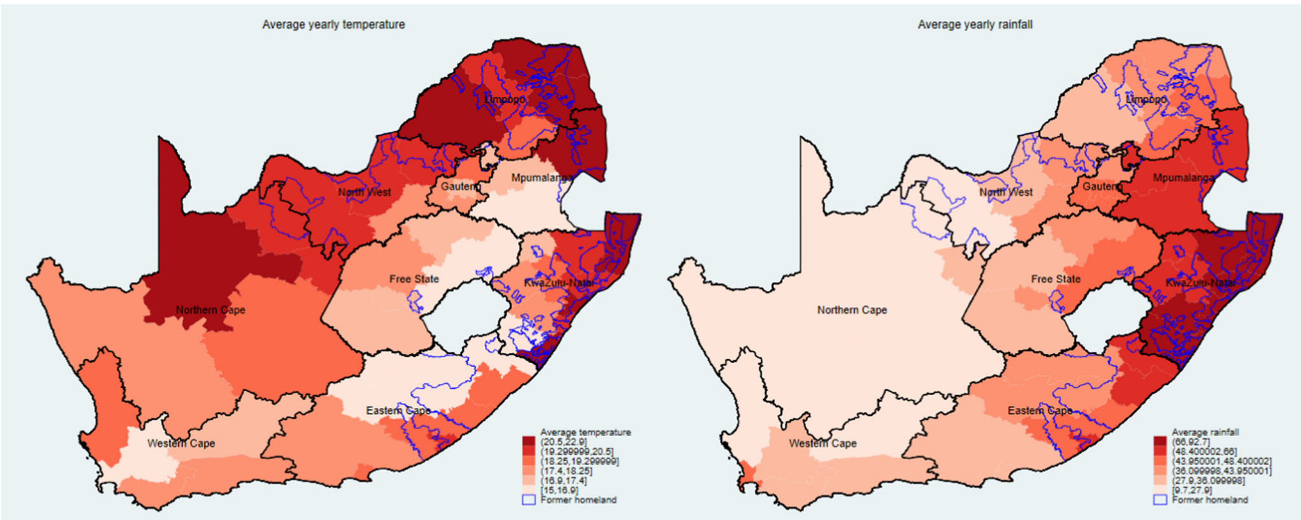

Fig. 2 Spatial distribution of average temperature and Precipitation across districts in South Africa, 2017. Source: The authors' calculation is based on aggregating climate data produced by the Climate Research Unit (CRU) at the University of East Anglia (see Harris et al. 2020) to 52 districts.

Table 3 Ordinary Least Squares regression poverty indicators dependent variable.

VARIABLES	Model 1 loghhpcc	Model 2 loghhpcinc	Model 3 Asset index	Model 4 hhupperpl
logtemperature	−0.244*** (0.058)	−0.185*** (0.063)	−0.161* (0.088)	0.057** (0.025)
lograinfall	−0.084*** (0.013)	−0.075*** (0.014)	−0.115*** (0.020)	0.028*** (0.006)
Constant	8.244*** (0.154)	8.130*** (0.169)	0.948*** (0.235)	0.168** (0.066)
Observations	7,135	7,135	7,039	7,135
R-squared	0.013	0.008	0.007	0.006
F-test	48.41	28.47	27.28	20.85
Prob > F	0	0	0	9.33e-10

Heteroscedasticity-consistent standard errors are in parentheses. Level of statistical significance:
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The dependent variables in all the columns are log household per capita consumption expenditure (loghhpcc), log income per capita (loghhpcinc), asset index and income poor variable (hhupperpl).
R-squared is the adjusted R-squared.

per capita consumption is negative. An increase in average temperature and rainfall is related to a decrease in household per capita consumption. Azzarri and Signorelli (2020), in a study focusing on Sub-Sahara Africa, concluded similar findings. The study found that higher average rainfall was associated with a decrease in household per capita consumption and prevalence of poverty. Specifically, they document that an additional one degree Celsius is linked to a 4.6% decrease in per capita consumption expenditure and a 2.8 percentage point rise in poverty rates. Moreover, their findings reveal that rainfall exceeding one standard deviation from the 50 year average is correlated with a 35% reduction in total and food per capita consumption, along with a 17-percentage point increase in extreme poverty.

To conduct a robustness check, we regressed climatic conditions variables on household per capita income, asset index (representing household asset holding) and the likelihood of being income poor (income poor).

The findings show that a 1% increase in temperature and precipitation leads to a 0.185 and 0.075% significant decrease in household per capita income, respectively. Turning on to the asset index, a 1% increase in temperature and rainfall leads to a 0.00161 and 0.00115% decrease in the household asset index, respectively. For income-poor households, one is more likely to be income-poor as temperature and precipitation increases. Income poor households have low resilience to extreme climatic conditions. The study results confirm the direct linear impact of climatic conditions on household per capita income, asset index, and income-poor households. The results show that the effect of precipitation on asset index and income-poor households is more significant than the effect of temperature. Angelsen and Dokken (2018) and Hallegatte and Rozenberg (2017) confirmed that climatic conditions can negatively affect household consumption, household income, and asset holding, propagating extreme poverty. According to Angelsen and Dokken (2018), individuals classified as income and asset-poor are 50% more likely to have encountered significant income shocks. The results from the study confirm a linear negative impact of climatic conditions on household per consumption, per capita income, and asset index. The study also confirms a positive linear relationship between climatic conditions and income-poor households. In Table 4, we present results comparing the OLS (Model 1) and quantile regression (Model 2-Q10 to Model 6-Q90) estimates for the main dependent variable (log household per capita consumption). In these regressions, we used local climatic conditions as the only independent variables.

For both the OLS and quantile regression models, the estimates are negative and statistically significant, suggesting that an increase in average temperature and precipitation is associated with a decrease in household per capita consumption. The OLS estimates indicate that a one percent increase in temperature (precipitation) is associated with a 0.244 (0.084) percent decrease in household per capita consumption. The QR results show that the magnitude of an increase in temperature and precipitation differs across the household per capita consumption distribution. Elasticities with respect to temperature are highest in Q25 (−0.275) and lowest in Q50 (−0.178). The findings imply that at the 0.75 and 0.25 quantiles, a 1% increase in temperature causes a 0.275 and 0.178% decrease in consumption, respectively. Typically, households with higher expenditures exhibit greater elasticities for goods luxury goods (beyond basic). When faced with limited food availability, the reduction in expenditure back to basic consumption is more pronounced for higher-income earners than lower-income earners, who predominantly consume at the basic level. For temperature elasticities, Q75 (−0.114) and Q25 (−0.076) have the biggest and lowest responsiveness, respectively. The rainfall elasticities are higher for high-consumption households Q75 and Q90.

The findings confirm a negative linear relationship between climatic conditions and household per capita consumption, as confirmed by Azzarri and Signorelli (2020). The OLS regression and QR estimates vary significantly, and this is visible in Fig. 3, which plots the OLS and QR coefficients and the associated 95% confidence intervals on the same graph.

Cognisant of the argument that a non-linear quadratic correlation exists between climatic conditions and household per capita consumption (Popoola et al. 2018), we envisage the prospect that favourable climatic conditions could enhance productivity and consumption. Accordingly, we regressed linear and quadratic (squared values) temperature and precipitation variables. The estimation results are presented in Table 5.

The regression results for temperature and per capita consumption are generally insignificant and inconsistent across the QR models. The 10th quantile regression model shows a concave relationship between household per capita consumption and monthly average temperature.[8] At low temperature levels, household per capita consumption increases and when temperature increases to 21,3 °C, household per capita consumption starts to decline. The results show that extremely high average monthly temperatures above 21,3 °C propagate poverty. In their study, Angelsen and Dokken (2018) showed that poor households are more likely to reside in regions with extreme temperatures, which are less conducive to production, resulting in poor consumption streams. Such households require tailor-made support that mitigates the reduction in consumption propagated by extremely warm conditions. The results from the 90th QR model show a convex relationship between household per capita consumption

Table 4 Ordinary Least Squares and Quantile Regression Model Estimates per capita consumption dependent variable.

		Quantile regression estimates				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VARIABLES	OLS	Q10	Q25	Q50	Q75	Q90
logtemperature	−0.244*** (0.058)	−0.216*** (0.070)	−0.275*** (0.064)	−0.178*** (0.069)	−0.260*** (0.097)	−0.254* (0.135)
lograinfall	−0.084*** (0.013)	−0.077*** (0.016)	−0.076*** (0.014)	−0.098*** (0.016)	−0.114*** (0.022)	−0.113*** (0.031)
Constant	5.699*** (0.353)	6.807*** (0.188)	7.486*** (0.172)	7.959*** (0.186)	9.069*** (0.261)	9.983*** (0.363)
Observations	7,135	7,135	7,135	7,135	7,135	7,135
F-test	4.079	25.59	35.92	33.10	25.45	12.73
Prob > F	0.0170	0.000	0.000	0.000	0.000	0.000

Notes: Heteroscedasticity-consistent standard errors are in parentheses. Level of statistical significance:
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The dependent variable in all the columns is the log household per capita consumption expenditure. For the OLS models, R-squared is the adjusted R-squared, while for Quantile regression models, R-squared is the pseudo-R-squared.

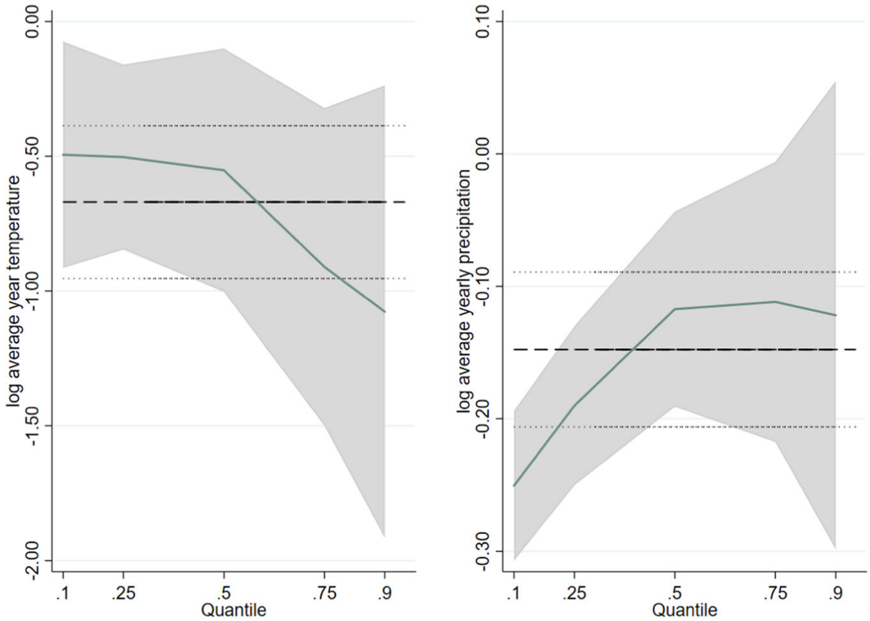

Fig. 3 Ordinary Least Squares and Quantile Regression Model Estimates showing the elasticity of consumption across the distribution. Source: Authors' graphical plots using Ordinary least squares and Quantile regressions estimates.

Table 5 Ordinary Least Squares and Quantile Regression Model Estimates per capita consumption dependent variable.

		Quantile regression estimates				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
VARIABLES	**OLS**	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
logtemperature	−0.289 (2.268)	−2.863** (1.433)	−0.554 (1.495)	1.544 (1.562)	3.195 (2.098)	8.700*** (3.122)
logtemperature2	0.045 (0.405)	0.468* (0.256)	0.055 (0.267)	−0.304 (0.279)	−0.610 (0.374)	−1.619*** (0.557)
lograinfall	0.235*** (0.090)	0.239*** (0.057)	0.189*** (0.059)	0.343*** (0.062)	0.371*** (0.083)	0.397*** (0.123)
lograinfall2	−0.054*** (0.015)	−0.055*** (0.010)	−0.048*** (0.010)	−0.075*** (0.010)	−0.083*** (0.014)	−0.085*** (0.021)
Constant	5.518* (3.133)	10.143*** (1.979)	7.537*** (2.065)	4.992** (2.158)	3.624 (2.899)	−2.950 (4.312)
Observations	7,135	7,135	7,135	7,135	7,135	7,135
F-test	6.742	27.41	24.66	26.89	21.67	13.04
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Heteroscedasticity-consistent standard errors are in parentheses. Level of statistical significance:
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The dependent variable in all the columns is log household per capita consumption expenditure and the independent variables are the linear and square variables of climatic conditions. For the OLS models, R-squared is the adjusted R-squared, while for Quantile regression models, R-squared is the pseudo-R-squared.

and temperature. The results show that when the average monthly temperature is below 4 °C, an increase in temperature leads to a decrease in household per capita consumption, while when the average monthly temperature increases beyond 4 °C, the household per capita consumption increases. The results show that people living in extremely cold areas need area-specific support to alleviate their household per capita consumption.

There is a significant convex relationship between household per capita consumption and average monthly regional precipitation for the OLS and all the quantile regressions across the whole distribution, as shown in Table 5. Below the minimum point, an increase in average monthly rainfall leads to a decrease in consumption and above the minimum, average monthly precipitation increases household per capital consumption. The results show that very low levels of average regional precipitation constrain per capita consumption streams of households. The results for the OLS regression model show that if average monthly rainfall is below 8,8 mm, an increase in precipitation results in a reduction in household per capita consumption. The results reveal that households in regions with yearly average precipitation below 105,6 mm (8,8 mm × 12 months) are likelier to have low consumption streams. Households living in areas with low rainfall have limited income generation opportunities (Leichenko and Silva, 2014). Agriculture production is usually not viable, leading to constrained household consumption patterns. Our results also show that, on average, in households in regions receiving yearly rainfall average above 105,6 mm, an increase in precipitation is associated with an increase in household per capita consumption.

The study analysed the impact of precipitation on the whole distribution of per capita consumption using QR models. The calculated yearly average precipitation turning points of the quadratic regressions for the 10th, 25th, 50th, 75th, and 90th quantiles are 104,4, 86,4, 117,6, 111,6 and 123,6 mm, respectively. An increase in precipitation below the turning point is associated with a decrease in per capita household consumption. Our results confirm the traditional mantra: ‘ water is life’. Beyond the turning point, an increased precipitation boosts per capita household consumption. The reason behind the findings could be that regions that receive higher levels of rainfall have more income-

Table 6 Ordinary Least Squares and Quantile Regression Model Estimates per capita income dependent variable.

		Quantile regression estimates				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VARIABLES	OLS	Q10	Q25	Q50	Q75	Q90
logtemperature	6.141 (4.299)	6.918*** (2.217)	4.525*** (1.701)	4.078*** (1.575)	2.726 (2.223)	5.318* (2.812)
logtemperature2	−1.095 (0.767)	−1.260*** (0.396)	−0.813*** (0.303)	−0.763*** (0.281)	−0.516 (0.397)	−0.987** (0.502)
lograinfall	−0.035 (0.170)	0.112 (0.088)	0.226*** (0.067)	0.316*** (0.062)	0.239*** (0.088)	0.381*** (0.111)
lograinfall2	0.006 (0.029)	−0.032** (0.015)	−0.055*** (0.011)	−0.069*** (0.011)	−0.058*** (0.015)	−0.081*** (0.019)
Constant	−3.739 (5.938)	−3.479 (3.063)	0.205 (2.349)	1.684 (2.175)	4.501 (3.071)	1.657 (3.884)
Observations	7,135	7,135	7,135	7,135	7,135	7,135
F-test	0.518	7.989	16.12	25.75	12.16	10.65
Prob > F	0.723	2.01e-06	0	0	7.50e-10	1.34e-08

Notes: Heteroscedasticity-consistent standard errors are in parentheses. Level of statistical significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The dependent variable in all the columns is log household per capita income. For the OLS models, R-squared is the adjusted R-squared, while for Quantile regression models, R-squared is the pseudo-R-squared.

Table 7 Ordinary Least Squares and Quantile Regression Model Estimates Assets index dependent variable.

		Quantile regression estimates				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VARIABLES	OLS	Q10	Q25	Q50	Q75	Q90
logtemperature	−4.942 (5.235)	8.477 (6.024)	3.984 (3.429)	6.569*** (2.295)	10.006*** (1.288)	3.127** (1.481)
logtemperature2	0.868 (0.934)	−1.476 (1.075)	−0.708 (0.612)	−1.225*** (0.409)	−1.821*** (0.230)	−0.566** (0.264)
lograinfall	−0.448** (0.206)	0.076 (0.237)	0.352*** (0.135)	0.565*** (0.090)	0.446*** (0.051)	0.097* (0.058)
lograinfall2	0.075** (0.035)	−0.054 (0.040)	−0.092*** (0.023)	−0.121*** (0.015)	−0.090*** (0.009)	−0.021** (0.010)
Constant	3.008 (7.232)	−14.127* (8.323)	−6.407 (4.737)	−8.622*** (3.170)	−12.653*** (1.779)	−2.271 (2.047)
Observations	7,039	7,039	7,039	7,039	7,039	7,039
F-test	1.696	4.563	11.89	34.10	65.12	3.660
Prob > F	0.148	0.00111	0.000	0.000	0.000	0.00554

Notes: Heteroscedasticity-consistent standard errors are in parentheses. Level of statistical significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The dependent variable in all the columns is the Asset index. For the OLS models, R-squared is the adjusted R-squared, while for Quantile regression models, R-squared is the pseudo-R-squared.

generating opportunities that help stimulate household per capita consumption. The study results confirm that climatic conditions significantly impact household consumption. Regions that receive very low rainfall in South Africa require area-specific support to boost their household per capita consumption. Interventions such as providing irrigation schemes, harnessing water and all-inclusive development support measures can mitigate the impact of low rainfall on household per capita consumption. The study further analysed the effect of climatic conditions on household per capita income and confirmed similar results.

There is a convex relationship between climatic conditions (temperature and precipitation) and household per capita income, as shown in Table 6. Although the study could not confirm significant results for the OLS model, QR models show that household per capita income declines at low levels of precipitation or temperature. Beyond the turning point, increased precipitation or temperature is associated with increased household per capita income. Several studies have confirmed evidence of a non-linear relationship between local climate conditions and other economic outcomes like labour supply, economic growth, and income (Antonelli et al. 2021; Shayegh et al. 2021; Zivin and Neidell, 2014).

Climatic conditions can have a bearing on the assets that a household can own. The study interrogated whether climatic conditions have a non-linear relationship with household asset ownership. The findings are presented in Table 7. The OLS model reveals a concave relationship between the asset index and precipitation. As precipitation increases, household asset holding increases below the average yearly precipitation turning point of 237,8 mm (19,8 mm×12 months). Above the annual average precipitation, an increase in rainfall is associated with a decrease in household asset holding. The results for the whole group show that excessive rain can be detrimental to household asset ownership.

On the contrary, our QR model results show a convex relationship between household asset ownership and climatic conditions (precipitation and temperature). The results from QR models Q25, Q50, Q75 and Q90 show significant turning points of average yearly rainfall of 81,3 mm (6,8 mm × 12 months), 123,9 mm, 143,0 mm, and 120,8 mm. Below the turning points, an increase in precipitation is associated with a decrease in the household asset index. Above the turning point, an increase in average yearly rainfall is related to an increase in household asset index. The weather services Department of South Africa estimates that the average annual rainfall for South Africa is 464 mm. Most rainfall is recorded in the Western Cape (June to August) and the rest of the country (December to February). Rainfall plays a vital role in enhancing households' well-being and can help generate income that will be used to acquire assets (Eichsteller et al. 2022). The study discovered a non-linear convex relationship between household asset index and average monthly temperature (Table 7).

The turning points for QR models Q50, Q75 and Q90 have the following average monthly temperatures: 15,4 °C, 15,6 °C, and

15,8 °C, respectively. An increase in temperature below the turning points is significantly associated with a decrease in the household asset index. In contrast, an increase in temperature above the turning points is associated with and increase in household asset index. The results show that very low temperatures do not provide a conducive environment for acquiring assets. Extremely cold temperatures can hamstring efforts to acquire assets.

The research also analysed the impact of vapour, wet days, and evapotranspiration on household consumption, Table 1B in the Appendix. The results from the three climatic conditions generally show that an increase in the three climatic conditions is associated with a decrease in household per capita consumption. The climatic condition 'wet days' is significant in the OLS and QR model analysis. The quadratic regression also confirms a convex relationship between wet days and household per capita consumption. Wet days below the turning point are associated with a decrease in household per capita consumption. Shows that a few wet days constrain other factors that promote an increase in household per capita consumption. However, an increase in wet days above the turning point is associated with an increase in household per capita income. Normal rainfall provides a conducive environment for producing goods and services, leading to better consumption levels.

The study further investigates whether regional climatic conditions impact household per capita consumption after controlling for household characteristics and the results are given in Tabe 8. The study found a weak impact of regional climatic conditions on household per capita consumption when household characteristics are included in the OLS and QR models. A temperature increase significantly reduces household per capita consumption for the 90th quantile (Q90), OLS and the 25th quantile(Q25) model. The study also found that an increase in precipitation is significantly associated with a decrease in household per capita consumption for Q10, Q50 and Q90 QR models. The results show that the impact of regional climatic conditions on household per capita consumption is minimal if we control for household characteristics. There are household characteristics significantly associated with the promotion of household per capita consumption and others significantly related to the reduction in household per capita consumption.

Household characteristics that were concluded to increase household per capita consumption are household average education, employed household head, total household debt and household asset index. To mitigate the impact of regional climatic conditions, the authorities must provide education and skills to citizens. Providing education and other life skills helps citizens to be productive in society, leading them to attain higher levels of consumption, thereby reducing poverty. People with higher levels of education have been confirmed to be more likely to lead better lives than those with less education (Dao, 2008). Consistent with existing literature, higher education levels increase household consumption (Banerjee and Duflo, 2007; Woolard and Klasen, 2005).

Gainfully employed people can grow their asset base. The study concluded that household per capita consumption also increases as the asset index increases. Households with an extensive asset stock are less likely to face starvation and malnutrition (Alderman et al. 2006). Total household debt is another household characteristic that significantly increases household per capita consumption. People with the capacity to hold debt are usually gainfully employed or have assets they use as collateral to accumulate debt. Debt allows people to consume goods and services immediately against their future income streams. Therefore, the ability to access debt can promote household per capita consumption, as confirmed by the study findings.

On the contrary, the study results show that household per capita consumption is more likely to decrease as the age of the household increases, when the household head is black or African when the head of the household is female, if the household has children under 6 years, as the household dependency ratio increases, and for people living in rural areas. In a context where climatic conditions weigh down on household per capita consumption, the welfare of people with the characters listed above is more likely to be impacted negatively. There is a need for authorities to design all-inclusive policies to mitigate the impact of declining household per capita consumption for such groups of people.

To investigate whether there is a non-linear relationship between household per capita consumption and climatic conditions after controlling for household characteristics, we included square rainfall and temperature variables. The results are shown in Table 8. The study findings show that the impact of climatic conditions is insignificant after controlling for household characteristics. The results show that the effect of climatic conditions on household per capita consumption can be mitigated by intervening in the household characteristics. The intervention by authorities can include promoting factors that improve household per capita consumption, such as the average household level of education, putting policies that help create employment, designing policies that help individuals build their asset base, and ensuring functional credit lines for households (Table 9).

Aside from the climatic conditions, the study concludes that as one gets older, black or African households, female-headed households, households with children under 6 years, higher dependency ratio, infrastructural and living in remote rural areas are associated with decreasing household per capita consumption. The life cycle hypothesis shows that older citizens struggle to make ends meet since they are more likely to be unemployed. There is a need to provide social welfare safety nets to older citizens. Other household groups that require targeted policies to improve household consumption are female head households, black African-headed households, rural households, and households with a huge dependency ratio.

Several studies have confirmed our findings. The revealed gender dimension to household welfare is in line with existing studies that find that, on average, female-headed households are more vulnerable to poverty than male-headed households (Flatø et al. 2017; Posel and Rogan, 2012). Gender disparities in the labour market might explain the low consumption for female-headed households. Females generally earn significantly less and have less access to economic opportunities than their male counterparts (Garza-Rodriguez et al. 2021). Having children under 6 years increases the chance of a household being in poverty (Azzarri and Signorelli, 2020). An increase in the dependency ratio tends to lower household welfare in South Africa and Uganda(Mduduzi Biyase and Zwane, 2018; Habyarimana et al. 2015). All these welfare challenges can have a magnified impact if adverse climatic conditions compound them.

Conclusion

This study sought to improve our understanding of the relationship between household poverty and local region-specific climate conditions in South Africa. Existing studies focusing on household poverty have examined the effects of traditional household factors. However, studies focusing on climate conditions are rare in South Africa. Climate plays a vital role in economic development, and as a result, it is necessary to study the effects of climate conditions on household poverty in South Africa. To this end, the study examined the effects of climate

Table 8 OLS and Quantile Regression Model Estimates per capita consumption dependent variable.

		Quantile regression estimates				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VARIABLES	OLS	Q10	Q25	Q50	Q75	Q90
logtemperature	−0.406* (0.220)	−0.080 (0.085)	−0.124* (0.073)	−0.005 (0.068)	−0.114 (0.073)	−0.254*** (0.094)
lograinfall	0.024 (0.049)	−0.038** (0.019)	−0.002 (0.016)	−0.028* (0.015)	−0.018 (0.016)	−0.040* (0.021)
hhhead_age	−0.008* (0.004)	−0.006*** (0.002)	−0.005*** (0.001)	−0.005*** (0.001)	−0.005*** (0.001)	−0.006*** (0.002)
hhhead_black	−0.178 (0.130)	−0.266*** (0.050)	−0.311*** (0.043)	−0.290*** (0.040)	−0.339*** (0.043)	−0.317*** (0.055)
hhhead_female	−0.184* (0.106)	−0.094** (0.041)	−0.146*** (0.035)	−0.153*** (0.033)	−0.170*** (0.035)	−0.059 (0.045)
hhmean_education	0.151*** (0.024)	0.155*** (0.009)	0.141*** (0.008)	0.141*** (0.007)	0.118*** (0.008)	0.093*** (0.010)
hhemployed	0.210 (0.148)	0.204*** (0.057)	0.134*** (0.049)	−0.020 (0.046)	−0.031 (0.049)	0.011 (0.063)
hhchild_under6	−0.408*** (0.120)	−0.462*** (0.046)	−0.548*** (0.040)	−0.616*** (0.037)	−0.728*** (0.040)	−0.777*** (0.051)
dependent_ratio	−0.097 (0.082)	−0.136*** (0.032)	−0.123*** (0.027)	−0.152*** (0.025)	−0.112*** (0.027)	−0.119*** (0.035)
rural	−0.071 (0.148)	−0.202*** (0.057)	−0.150*** (0.049)	−0.176*** (0.046)	−0.157*** (0.049)	−0.189*** (0.063)
pc_infrast	−0.101 (0.081)	−0.052* (0.031)	−0.064** (0.027)	−0.074*** (0.025)	−0.099*** (0.027)	−0.153*** (0.034)
lhhdebt	0.094*** (0.027)	0.127*** (0.010)	0.134*** (0.009)	0.150*** (0.008)	0.160*** (0.009)	0.155*** (0.011)
asset_index	0.283*** (0.056)	0.175*** (0.022)	0.192*** (0.019)	0.178*** (0.017)	0.184*** (0.019)	0.232*** (0.024)
Constant	5.141*** (0.733)	4.805*** (0.283)	5.393*** (0.243)	5.628*** (0.227)	6.620*** (0.244)	7.816*** (0.312)
Observations	3,444	3,444	3,444	3,444	3,444	3,444
F-test	28.31	192.5	259	304.7	257.1	149.8
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Heteroscedasticity-consistent standard errors are in parentheses. Level of statistical significance:
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The dependent variable in all the columns is log household per capita total consumption expenditure. For the OLS models, R-squared is the adjusted R-squared, while for Quantile regression models, R-squared is the pseudo-R-squared.

Table 9 OLS and Quantile Regression Model Estimates per capita consumption dependent variable.

		Quantile regression estimates				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VARIABLES	OLS	Q10	Q25	Q50	Q75	Q90
logtemperature	−5.845 (5.250)	−0.571 (1.886)	−1.387 (1.641)	−1.865 (1.580)	−1.122 (1.666)	−1.704 (2.188)
logtemperature2	0.984 (0.938)	0.079 (0.337)	0.225 (0.293)	0.330 (0.282)	0.181 (0.298)	0.260 (0.391)
lograinfall	−0.050 (0.209)	−0.118 (0.075)	−0.106 (0.065)	−0.044 (0.063)	−0.031 (0.066)	0.085 (0.087)
lograinfall2	0.013 (0.036)	0.016 (0.013)	0.019* (0.011)	0.003 (0.011)	0.002 (0.011)	−0.022 (0.015)
hhhead_age	−0.008* (0.004)	−0.005*** (0.002)	−0.005*** (0.001)	−0.004*** (0.001)	−0.005*** (0.001)	−0.005*** (0.002)
hhhead_black	−0.251* (0.136)	−0.280*** (0.049)	−0.330*** (0.043)	−0.282*** (0.041)	−0.342*** (0.043)	−0.303*** (0.057)
hhhead_female	−0.161 (0.110)	−0.110*** (0.040)	−0.149*** (0.035)	−0.158*** (0.033)	−0.166*** (0.035)	−0.064 (0.046)
hhmean_education	0.141*** (0.025)	0.152*** (0.009)	0.141*** (0.008)	0.142*** (0.007)	0.116*** (0.008)	0.092*** (0.010)
hhemployed	0.184 (0.155)	0.211*** (0.056)	0.121** (0.048)	−0.014 (0.047)	−0.032 (0.049)	0.010 (0.064)
hhchild_under6	−0.369*** (0.125)	−0.453*** (0.045)	−0.559*** (0.039)	−0.617*** (0.038)	−0.735*** (0.040)	−0.783*** (0.052)
dependent_ratio	−0.072 (0.086)	−0.144*** (0.031)	−0.130*** (0.027)	−0.154*** (0.026)	−0.108*** (0.027)	−0.114*** (0.036)
rural	−0.132 (0.155)	−0.192*** (0.056)	−0.156*** (0.049)	−0.182*** (0.047)	−0.160*** (0.049)	−0.165** (0.065)
pc_infrast	−0.112 (0.085)	−0.045 (0.030)	−0.064** (0.027)	−0.072*** (0.026)	−0.098*** (0.027)	−0.148*** (0.035)
lhhdebt	0.080*** (0.028)	0.127*** (0.010)	0.133*** (0.009)	0.149*** (0.008)	0.159*** (0.009)	0.156*** (0.012)
asset_index	0.273*** (0.059)	0.171*** (0.021)	0.192*** (0.018)	0.178*** (0.018)	0.189*** (0.019)	0.232*** (0.024)
Constant	12.986* (7.273)	5.662** (2.613)	7.309*** (2.274)	8.215*** (2.188)	8.060*** (2.308)	9.623*** (3.030)
Observations	3,444	3,444	3,444	3,444	3,444	3,444
F-test	19.64	175.6	233.4	259.1	224.9	124.7
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Heteroscedasticity-consistent standard errors are in parentheses. Level of statistical significance:
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The dependent variable in all the columns is log household per capita consumption expenditure. For the OLS models, R-squared is the adjusted R-squared, while for Quantile regression models, R-squared is the pseudo-R-squared.

conditions, measured as variability in local temperature and precipitation, on household poverty measured by the per capita consumption of South African households in 2017. The study used household survey data—the 2017 NIDS, wave 5 data and climate data produced by the Climate Research Unit (CRU) at the University of East Anglia.

The empirical analysis in this paper showed that household poverty, measured by per capita consumption and climate conditions, measured by temperature and precipitation, vary significantly across regions in South Africa. Further, the exploratory analysis showed a spatial coincidence between household per capita consumption and climate conditions. An increase in precipitation is associated with a decrease in per capita consumption in the OLS and QR models. The quadratic regression models show a convex relationship between precipitation and household per capita consumption, showing that consumption increases in log of rainfall and decreases in log of rainfall squared. Low levels of rainfall are associated with low levels of household per capita consumption and higher levels of rainfall beyond the turning point are associated with higher levels of household per capita consumption. The study also confirmed similar results when the relationship between household per capita income and local regional temperature was analysed. The linear relationship shows that an increase in temperature is associated with a decrease in household per capita income. Our results show that the relationship between average monthly rainfall with household per capita consumption, household per capita income and asset index is more consistent than that of average monthly temperature and the same variables.

Climatic conditions also influence household asset ownership. An increase in rainfall or temperature is associated with a decrease in the asset index. The OLS quadratic regression shows a concave relationship between climatic conditions (precipitation and temperature) and the household asset index. The household asset index decreases in log of rainfall and increases in log of rainfall squared, showing that for the whole sample, an increase in rainfall decreases the household asset index beyond the turning point. On the contrary, quadratic regression across the distribution, that is, quantile regression, shows that the household asset index is increasing in log of rainfall and temperature and decreasing in log of rainfall and temperature squared. Below the turning point, an increase in rainfall and temperature is associated with a decrease in the household asset index, above the turning point, an increase in rainfall and temperature is related to an increase in the household asset index.

The study findings show that regions with harsh climatic conditions in South Africa have generally low consumption expenditure in households. This reveals that household poverty can be contextual or neighbourhood confined, propagated by climatic conditions. Harsh climatic conditions such as low rainfall and extreme temperatures impact consumption patterns of households in South Africa. The study results assist in explaining the impact of harsh climatic conditions on stability, accessibility, insecurity and utilization of household consumption expenditure in South Africa. Based on the study results, regions receiving low rainfall in South Africa require area-specific support, such as harnessing water and providing irrigation schemes to alleviate household consumption. Areas experiencing extreme temperatures (very cold or very hot) in South Africa require tailor made intervention to alleviate consumption expenditure of households.

When we controlled for household characteristics in the linear and quadratic regressions across the OLS and QR models, the impact of climatic conditions on household per capita consumption faded. Household characteristics play an essential role in mitigating the effects of climatic conditions on household consumption. Wealthier households are less affected by climatic conditions than poor households. Policies that promote increased consumption can mitigate the impact of local region climatic conditions. These include wealth accumulation (increase in asset index), increase in skills (average household education), creation of employment (head of household employed), sustainable credit lines (total household debt), well-being and productivity. In addition, there must be tailor-made policies to alleviate the welfare of disadvantaged groups such as female-headed households, household heads that are black, rural citizens, households with a high dependency ratio and improved service delivery across the economy.

The study focused on a cross-sectional analysis of the impact of climatic conditions on household per capita consumption. A panel data or a time series analysis can clarify the impact of climatic conditions on household per capita consumption. There is a need to investigate the impact of climate variability and shocks by regions in South Africa. The advent of floods, excessive rainfall, damaging windy conditions, hailstorms, extreme temperatures, and continued drought are some of the climatic conditions that require regional-specific analysis.

Data availability

Publicly available datasets were utilised in this study. There is no need for consent and ethical clearance. This data can be found from DataFirst at the University of Cape Town, South Africa (https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/712/related-materials) and the Climate Research Unit (CRU) at the University of East Anglia, England (https://www.uea.ac.uk/web/groups-and-centres/climatic-research-unit/data). We also posted the consolidated data on: local climatic conditions on household consumption. A case of South Africa—Mendeley Data and Harvard Dataverse: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FSAO4CV&version=DRAFT

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Notes

1 Of these studies, Flatø et al.(2017) finds that a one standard deviation decrease in Precipitation reduces income for female-headed households by about 1.7% compared to 0.2% for dual-headed households, Shayegh et al. (2021) finds that climate change has a negative impact on the economy and welfare as output per adult drops by 20% due to an increase in temperature, while Dasgupta et al. (2020) finds that an increase in temperature leads to between three and four points increase in income inequality compared to scenario without temperature increase.

2 We get the climate data at district level by combining the grid-level roster file containing climate data with the district-level shapefile containing the polygons of each district. Using QGIS, we then extract average monthly climate data for each district based on the centroid—latitudes and longitudes for each district. Finally, we sum the average monthly climate data and divide by twelve months to get the average yearly climate data for each district.

3 To derive per capita income for a household, total income was divided by the number of individuals in the household.

4 This upper-bound poverty line refers to the food poverty line plus the average amount derived from non-food items of households whose food expenditure is equal to the food poverty line. Statistics South Africa estimates the upper-bound poverty line at R1 138 per person per month in April 2017 prices.

5 In other words, the estimates represent the elasticity of household per capita consumption with respect to a given local climate variable.

6 A robustness check was done for our main analysis where we remove the child-headed households, and our main results and conclusions did not change.

7 The pairwise correlations are statistically significant ($p < 0.01$). While the correlations between household welfare measures are high suggesting that these measures are good predictors of each other, the correlations between climate variables are low, mitigating concerns of multicollinearity among the climate variables, Table 1A.

8 To estimate the local climate conditions threshold, beyond which local climate conditions hurts the household consumption, we differentiate Eq. 1 and 2 with respect to temperature and precipitation and set it to 0. $\frac{\partial[\beta_1 lntemperature - \beta_2 lntemperature^2]}{\partial \mathrm{lntemperature}} = 0$ and $\frac{\partial[\delta_1 lnrainfall - \delta_2 lnrainfall^2]}{\partial rainfall} = 0$. Finally, we find the maximum average annual temperature and precipitation by solving for temperature and precipitation as follows:$\mathrm{T} = e^{(\frac{\beta_1}{2\beta_2})}$ and $\mathrm{P} = e^{(\frac{\delta_1}{2\delta_2})}$.

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Conceptualization, Getrude Jana (GJ), Calvin Mudzingiri (CM), Gibson Mudiriza (GM) and Regret Sunge (RS); Methodology, GM and CM; Software, GM and CM; Validation, CM.; Resources, CM.; Writing—original draft, GM; CM; RS, and GJ; Writing—review & editing, CM, GM, RS, and GJ. All authors have read and agreed to the published version of the manuscript.

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Ethical approval

National Income Dynamics data received ethical approval. For more information visit: http://www.nids.uct.ac.za/

Informed consent

All respondents completed the consent form. For more information visit: http://www.nids.uct.ac.za/

Competing interests

The authors declare no competing interests.

Additional information

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