GSJ: Volume 10, Issue 12, December 2022
ISSN 2320-9186

Global Scientific JOURNALS

GSJ: Volume 10, Issue 12, December 2022, Online: ISSN 2320-9186
www.globalscientificjournal.com

SOCIOECONOMIC IMPACT OF CLIMATE CHANGE: EVIDENCE FROM SOUTH AFRICA

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Abstract

Climate change is a global phenomenon that continues to pose a major threat to all aspects of life. Review of past and present studies shows limited empirical studies on the subject. Particularly, the socioeconomic impact of climate change has not been extensively explored globally and in South Africa. In this paper, we investigate the relationship between climate change (precipitation and temperature), poverty and inequality using agricultural income as the transmission mechanism via the Ricardian model. Findings from the first stage analysis through the Ricardian model show that changes in temperature and precipitation are significantly associated with changes in agricultural income. Further analysis reveals that climate change is associated with higher poverty and inequality. Based on the findings, it is recommended that promoting climate change adaptation capacity of poor households should be a priority as these households are more exposed to adverse impacts of climate change.

GSJ: Volume 10, Issue 12, December 2022
ISSN 2320-9186

Keywords: Climate Change; Socioeconomic Impact, Poverty, Inequality, Agricultural household; Ricardian model

1. Introduction

Globally, there is growing evidence that climate change has a far-reaching effect on all facets of humanity. The effect is predicted to continue in the future with more intensity, throwing socioeconomic life into danger. The magnitude and effect of climate change vary from country to country, with developing, low and middle-income countries more prone to its adverse consequences. McGuigan, Reynolds and Wiedmer (2002) predicted that the climate change impacts are more likely to be intense for developing countries with relatively high level of poverty and inequality. For these countries, climate change could exacerbate the existing socio-economic problems, especially in the rural communities where the livelihood such as agriculture is heavily climate dependent. López-Feldman and Rivera (2018), Fothergill and Peek (2004) and Winsemius et al. (2015) documented that poor rural households are more susceptible to the adverse impact of climate change and encounter more difficulties in recovery from the impact of climate. Climate change has despairing impact as COVID-19 (Geiger, Gore, Squire, & Attari, 2021) which has affected many facets of life (Anakpo, and Mishi, 2021, 2022; Gqoboka, Anakpo, & Mishi, 2022; Jafta, Anakpo, & Syden, 2022; Komanisi, Anakpo, & Syden, 2022; Tshabalala, Anakpo, & Mishi, 2021). Furthermore, there is a growing concern that the menace of rural poverty may be exacerbated due to climate change since the main livelihood activities such as agriculture are heavily climate dependent (Skoufias et al. 2011; Winsemius et al. 2015). Several empirical studies suggest that the effects of climate change will not be uniform across the globe. In South Africa, climate impact' studies are limited and focused mainly on the maize crop or some selected crops

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(Gbetibouo and Hassan, 2005). Evidence from Global Models developed so far suggests that the agricultural sector in the Southern Africa region is highly sensitive to future climate shifts and increased climate variability (Gbetibouo and Hassan, 2005).

South Africa is reported to have a unique position in terms of climate change in Sub-Saharan Africa and is the thirteenth largest contributor to climate change (Lin, Beidari and Lewis 2015; Neville, 2010)[1]. The country is also documented to have been experiencing high climate variability in the continent ranging from increasing temperature, drought, and erratic precipitation (Mahlalela, Blamey, Hart and Reason, 2020; Neville, 2010). This trend is expected to get worse, with persistent temperature variation from 1℃ to 3℃ by 2020 and erratic precipitation (Department of Environmental Affairs and Tourism, 2005) and this was confirmed in recent studies (Mbokodo, Bopape, Chikoore, Engelbrecht, and Nethengwe, 2020; Mahlalela et al, 2020). Consequently, households whose livelihood depend on agriculture may be significantly affected in terms of household income and other socioeconomic indicators such as poverty and inequality. Understanding the socioeconomic effects of climate change for such households is therefore important in informing short- and long-term planning and policymaking.

This paper investigates the socioeconomic impacts of climate change in South Africa at the household level. Climate change affect agricultural output and income level especially for poor and rural households. This has a knock-on effect on poverty and inequality (by changing agricultural yield for example) or affects other aspects of the economy such as reducing investment and labour productivity. In this paper, we focus on the former based on the established findings,

[1] This has to do with the emission of carbon dioxide

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we use quantitative analysis to examine the impact of climate change on poverty and inequality. First, for agricultural households and then how it translates to the overall poverty and inequality levels nationally. This study is particularly important due to the recent changes in climate which raise research and policy concern on possible socioeconomic implications.

It has been well established that climate change has direct impacts on agriculture. This can affect those whose livelihoods heavily depend on agriculture especially those living in rural areas. For instance, very hot or cold temperature or heavy precipitation or drought can significantly affect agricultural factors of production which may significantly reduce yield and invariably affect agricultural income directly and total income indirectly. Furthermore, due to heterogeneity, rural household's response to climate change may vary, for example, poorer households may be more limited in their ability to respond or adapt to climate change and this may further worsen the wellbeing of these households and life outcomes of its members (Anakpo & Kollamparambil, 2019, 2021a; 2021a). This does not only exacerbate poverty but could also widen inequality gaps. The effect of climate change has been estimated in the literature in many ways.

The existing literature provides quantitative evidence of different techniques for estimating the magnitude of climate impacts. First, some of these estimations are based on agronomic theory, which is also known as production function approach (Kahn et al. 2019). These techniques estimate climate impact indirectly from the production function by using labour as a transmission mechanism (Kahn et al. 2019) or by carefully controlling crop simulation experiments that estimate damages caused by variation in inputs such as temperature, precipitation on crop growth (Rosenzweig and Parry 1994). While this methodology is a good improvement over arbitrary correlation by having an underlying theory for estimation, economists assert that "agronomic

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studies tend to overestimate negative climate impacts and underestimate positive impacts because they fail to account for adaptations that farmers continuously undertake to cope with climate pressures" (Mendelsohn, Basist, Kurukulasuriya and Dinar, 2007; Adams et al 1990; 1999; Mendelsohn., Nordhaus, and Shaw, 1994; Mendelsohn, and Dinar, 1999). Mendelsohn et al. (2007) documented that "the agronomic studies ignore that sufficient reductions in yields will lead farmers to switch to a different crop that will better suit the new climatic conditions. Similarly, any positive impacts of climate change are likely to be underestimated in an agronomic model because it does not account for the behavioural response of farmers not producing the optimal crop who will switch into cultivating the optimal crop". To address this weakness, Mendelsohn et al. (1994) propose an alternative economic estimation strategy, known as the Ricardian method, that makes use of cross-sectional data in estimating the effect of climate change and also controlling for other covariates (such as socioeconomic factors and input use for the estimation).

The Ricardian technique offers more flexibility by reflecting farmers' rational response to climate change. Operationally, the Ricardian method accesses agricultural income or land value as a function of climate change and other covariates that are associated with the former. This estimation technique has been applied in different countries with different economic conditions. For instance, Mendelsohn and Dinar (2003) and Mendelsohn et al (1994) used Ricardian methodology in climate impact estimation in the United States; Maddison (2000) used the same technique to model climate impact in England and Wales; Mendelsohn et al (2001) and Dinar et al (1998) in India and Molua (2002) in Cameroon at aggregate district and farmers level. However, Ricardian cross-sectional technique alone fails to factor time elements of the data and may sometimes be associated with the

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problem of reverse causality when there is a feedback effect as normally associated with CO_2 (Carbon dioxide).

Thirdly, others used panel analytic models such as fixed effect methodology to estimate the impacts of climate change under the assumption that climate change is strictly exogenous thus ruling out any possible reversal effect from the outcome variables of interest (for instance economic variable) to the climate variables such as temperature (Kahn et al. 2019; Burke, Hsiang, and E. Miguel, 2015; Dell, Jones, and Olken, 2012; 2014; Hsiang, 2016). For instance, in their panel data analysis of 52 countries, Winsemius et al. (2015) found that the poor are more prone to the adverse effects of climate-related events such as flood and drought, especially in urban areas. Additionally, Yamamura (2015) applied the panel analytic technique to investigate the incidence and effects of natural disaster and found that although natural disaster has adverse effects on income and inequality in the short run, its effects are insignificant or disappear in the long run. In his computable general equilibrium work on the climate change impact analysis, Nordhaus (1992) documented that a fast pace of economic activities and growth increases greenhouse gas emission which in turn causes a rising level of temperature. At the same time the increasing level of temperature also adversely affects economic activities and economic growth. Kahn et al. (2019) reported that "when estimating the impact of climate change on economic growth, temperature may not be considered as strictly exogenous, but merely weakly exogenous or predetermined to income growth; in other words, economic growth in the past might have feedback effects on future temperature"

Furthermore, Mideksa (2010), applied "a computable general equilibrium model (CGE)" technique to examine the effects of climate change on inequality in Ethiopia. His study found that

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climate change increases inequality by 20%. Other studies that applied the above methodology include Hertel, Burke, Lobell (2010) and Ahmed, Diffenbaugh, Hertel (2009) but focusing on the impact of climate change on poverty in some developing countries. Ahmed et al. (2009), found that extreme adverse climate events cause productivity shock that contributes to the rising poverty level in Africa. Hertel et al. (2010) found that the rate of poverty for non-agriculture household increases by 20-50%.

More recently, the Ricardian model was applied to examine the impacts of climate change (López-Feldman, and Rivera, 2018; Kahn et al. 2019; Thapa, and Joshi, 2010; Jacoby, Rabassa and Skoufias, 2011). López-Feldman and Rivera (2018) applied the Ricardian method to analyse the impacts of climate change on key indicators such as poverty and inequality (with simulated climate data), the study examines how poverty and inequality vary under various climate change scenarios. They concluded that climate change significantly increases poverty and inequality at the national and regional level in Mexico. Jacoby et al. (2011) applied the Ricardian model (with some modification) to look into how climate change affects land, labour and food prices. They find that poverty rate at the national level in India would rise by 3.5 % by 2040, due to the impact of climate change.

In this paper, we examine the impact of climate change on poverty and inequality in South Africa using agricultural income as a transmission mechanism. We first looked into the poverty and inequality for the agricultural households and then how it translates to the overall poverty and inequality levels of all the households (i.e., nationally). This question is particularly relevant in the South African context, where poverty and inequality level are among the highest in World (Francis and Webster, 2019) with significant variability in climate especially over the past decades (Neville,

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2010). The study consolidates the existing quantitative methodology on climate impact literature with the observed dataset thus contributing to the literature.

2. Materials and Method

2.1 Data

The data for the analysis in this paper were obtained from two sources: National Income Dynamics Survey (NIDS) data collected from 2008 to 2016 in approximately 2 years intervals and the climate data that was obtained from South Africa weather service[2]. NIDS is a nationally representative study conducted by the South African Labor and Development Research Unit (SALDRU at the School of Economics, University of Cape Town, South Africa). Information on household characteristics is based on wave 4 of NIDS data collected in 2014 due to data constraints. This study firstly focuses on the agricultural households (household whose main subsistence strategy is agriculture such as crops and animals) since it is well established that agriculture is directly affected by climate change which in turn affect other aspects of socioeconomic life. The study used a total of 8970 households from NIDS data for 2014, out of which about 8.1% constitute agricultural households. These data contain relevant information particularly on the agricultural outcomes (including agriculture income from crops and animals), income, household characteristics including household size, age of the head and educational level of household's head. Concerning climate variables, average of monthly data on temperature and precipitation data were collected according to the four climatic seasons[3] in South Africa (that is, Summer, Autumn/Fall, Winter and Spring) for all the locations in the local district municipalities in which households'

[2] Through https://en.tutiempo.net/climate/south-africa.html and https://www.weathersa.co.za/

[3] Roughly speaking, the summer months are December to February, Autumn is March to May, Winter is June to August, and spring is September to November in South Africa.

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agricultural activities at the respective times of production take place so that climate change impact could be properly related to the production at that specific point in time. The average seasonal data on climate variables (Summer, Autumn/Fall, Winter and Spring) were collected for 2014 and 2016. The climate data include district names and codes which made it possible to match the district names and codes supplied by NIDS.

2.2 Estimation strategy

The existing literature has established the relationship between agricultural activities, specifically, agricultural income and climate change (López-Feldman, and Rivera, 2018; Mendelsohn et al. 1994, 1996, 2001). Additionally, ample empirical evidence shows that rural income is negatively affected through the transmission of agriculture income (Mendelsohn, Basist, Kurukulasuriya and Dinar 2007). While the existing literature also documents other means of transmission, agriculture income is reported to be a direct transmission mechanism, and this estimation methodology has been well investigated in the extant literature (Mendelsohn 2009). This paper estimates the effects of climate change (precipitation and temperature) on poverty and inequality using agricultural income as a transmission mechanism through a Ricardian model. This method implicitly incorporates private adaptation to climate conditions in the model by assuming that farmers are rational decision-makers and will therefore seek to maximize return by adopting climate adaptation measures in their operations (Di Falco, Veronesi, and Yesuf, 2011; Di Falco, Yesuf, Kohlin and Ringler C 2012; Di Falco and Veronesi, 2012).

This paper applied the quantitative procedure used by López-Feldman, and Rivera (2018) to investigate the association between climate change and poverty and inequality. López-Feldman and Rivera (2018) applied a Ricardian model to directly estimate the effects of climate change on

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poverty and income inequality (in Rural Mexico). The authors estimated the Ricardian model (i.e. a model that establishes the relationship between per capita household's agricultural income, climate change) and other covariates using rural household survey data observed in 2003. They then used climate models to simulate future climate data, and using the simulated data, counterfactual agricultural income was predicted using estimated coefficients from the Ricardian model under the assumption that household characteristics and other covariates remain the same. By summing up (predicted) agricultural and non-agricultural income, per capita household income was derived, the estimated counterfactual distribution of income was then used to estimate poverty and income inequality. By comparing the observed and the counterfactual distribution in terms of poverty and inequality, López-Feldman and Rivera (2018) estimated the impact of climate change on household income.

In other words, since the only difference between the counterfactual household per capita income and the observed per capita income is the simulated climate variables, the difference between poverty and inequality figures can be attributed to climate change.

We depart from the methodology in López-Feldman, and Rivera (2018) by using observed climate data for 2 years after our baseline (i.e. 2014 NIDS data) instead of the simulated data used in the study by López-Feldman and Rivera (2018). There are some reasons why one may want to take this approach (1) Results based on Simulated climate data can only be as good as the climate model on which the simulation is based, to the extent that these model cannot be completely accurate, using realized data points may be preferable (2) Getting access and using climate simulated data may not be easy for researchers from other fields since they lack a basic understanding of how these models are formulated and the limitation that can be associated with using them. On the other

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hand, using observed data can be seen as disadvantageous because it provides only one counterfactual per time. For example, López-Feldman, and Rivera (2018) used three different models to simulate counterfactual climate data.

The baseline for our analysis is 2014, instead of simulated climate data we use observed climate variables for 2016 as our counterfactual (climate variable). Specifically, we interpret our result as the effect of climate change on poverty and inequality in 2014 if climatic conditions are that of 2016. Our main hypothesis is that since climatic condition in South Africa is expected to get worse over time (Neville, 2010), one can expect climatic conditions in 2016 to have a more deleterious effect on poverty and inequality than prevailing conditions in 2014. Another way to look at this is to note that the Ricardian model accounts for adaptations that farmers continuously undertake to cope with climate pressures. However, the adaptations that are successful in 2014 may not be effective in 2016 (assuming that 2016 climatic conditions are worse).

. The non-linear relationship between climate change variables and agriculture income based on the Ricardian model is specified below.

$$AgIncome_i = \beta_O + \sum_{j=1}^{4} \beta_{1j}\, tem_{ji} + \sum_{j=1}^{4} \beta_{2j}\, tem_{ji}^{\;2} + \sum_{j=1}^{4} \beta_{3j}\, prec_{ji} + \sum_{j=1}^{4} \beta_{4j}\, prec_{ji}^{\;2} + \varepsilon \qquad [1]$$

$AgIncome_i$ denotes per-capita agricultural income of household, tem and $prec$ represent temperature and precipitation respectively. The household in the model is denoted by i while j indicates the number of seasons for each climate variable (that is, Summer, Autumn/Fall, Winter and Spring seasons). X denotes a vector of household characteristics such as provincial location, race, education, head composition, age, farm inputs used among others. $\beta_{1,}\beta_{2,}\beta_{3,}$ and $\beta_{4,}$ are the

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parameters of interest, which describe the relationship between climate variables and Agricultural income using the baseline data (i.e. 2014 in our case).

The use of cross-sectional data to describe this relationship is not without limitation (Deschenes and Greenstone, 2007), however, this model has been proven to be an effective econometric approach to explain and estimate the effect of climate change on the agricultural income especially in the developing countries (López-Feldman, and Rivera,2018; Mendelsohn et al., 2010)

In the second stage, the estimated coefficients (from the model [1]) were used with the observed climate data in 2016 to predict agricultural income (for agricultural households), under the assumption that household behaviour does not change over time. By doing so, changes in agricultural income between the observed and the counterfactual is linked to climate change (López-Feldman, and Rivera,2018). Thus, the counterfactual agriculture income was estimated according to the model specification below.

$$AgIncome_i{}^{ww} = \hat{\beta}_0 + \sum_{j=1}^{4} \hat{\beta}_{1j}\, tem_{ji}{}^{ww} + \sum_{j=1}^{4} \hat{\beta}_{2j}\, (tem_{ji}{}^{ww})^2 + \sum_{j=1}^{4} \hat{\beta}_{3j}\, prec_{ji}{}^{ww} + \sum_{j=1}^{4} \hat{\beta}_{4j} (prec_{ji}{}^{ww})^2 + \hat{\gamma} X + \varepsilon \qquad [2]$$

Where $AgIncome_i{}^{ww}$ is the predicted agricultural income, $\hat{\beta}_{ij}$ are the estimated parameters from equation [1], temperature ($tem_i{}^{ww}$) and precipitation ($prec_i{}^{ww}$) are observed climate data in 2016.

The total (counterfactual) per capita household income is the sum of income derived from agricultural and non-agricultural activities (that is $Income_i{}^{ww} = AgIncome_i{}^{ww} + Non -$

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$AgIncome_i$). Using the observed and the counterfactual distribution of income, population-weighted poverty and inequality measures were estimated and compared and changes ascertained.

In this paper, we applied the FGT (Foster–Greer–Thorbecke) poverty index suggested by Foster et al. (1984) specified as follows

$$FGT(\alpha) = \frac{1}{N}\sum_{i=1}^{N} I_i \left(1 - \frac{Income_i}{q}\right)^{\alpha} \quad [3]$$

Where I_i is 1 if $Income_i \leq$ q and 0 otherwise. $Income_i$ is defined as per capita income while q and N denote poverty line and population size, respectively. Consequently, poverty headcounts were estimated using three poverty lines[4]: food poverty line, lower-bound line and upper-bound line.

We also calculate the Gini Coefficient (G) according to the most widely used technique in academia and public policy as follows

$$G = \frac{-(N+1)}{N} + \frac{2}{N^2 \mu_{Income}} \sum_{i=1}^{N} i.Income_i \quad [4]$$

Where $Income_i$ represents per capital income (ordered from the lowest to the highest). μ_{Income} denotes average income (Fields 2001). The Gini coefficient of 0 means there is no inequality (that is perfect equality) and a value of 1 means perfect inequality.

[4] [4] Food poverty line, lower and upper bound were given at R417, R613, and R942 respectively at 2014 (Statistics South Africa, 2020).

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3. Results

Table 1 displays the summary statistics of the key variables of the study. This comprises the mean of climate variables (temperature and precipitation) which are operationalized according to the four major seasons (summer, fall, winter and spring) in South Africa, outcome variables (household income) and household characteristics such as provincial location, race, education, head composition, age, farm inputs used among others. The average temperature recorded in Summer, Autumn/Fall, Winter and Spring were 23.0℃, 18.6℃, 13.0℃ and 17.8℃ respectively in 2014 (Table 1A). Temperature was highest in Summer but least in the Winter. The trend is similar for 2016 temperature statistics with Summer recording the highest at 23.1℃, followed by Autumn/Fall (19.5℃), Spring (18.4℃) and the lowest being the winter temperature (14.0℃). Concerning the average precipitation, Summer season recorded the highest volume of precipitation (65.7mm) followed by Autumn/Fall (33.9mm) and then Spring and Winter recording 32.1mm and 3.9 mm respectively in 2014. Similarly, in 2016, Summer recorded the highest (87.95mm) followed by Spring (46.2mm) and Autumn/Fall (18.7mm) with the least precipitation recorded in Winter (3.8mm). It is noteworthy to see that the climate variables, in general, are higher and more variable in 2016 relative to 2014, this indicates that our assumption that climate conditions are worsening and more variable over time is consistent with our data.

Table 1B documents summary statistics of household characteristics. Average per capita household’s agricultural and nonagricultural income was estimated at R195.41 and R 1383.64, respectively. The table shows that most households were of African race (98.2%) with an average age of 56.3 years for the household head (about 34.6% of households are male-headed). In terms of the provincial distribution of households, KZN has the highest proportion with 45.3%, followed

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by Limpopo (20.2%) and then Eastern Cape (13.3%) while Northwest recorded the least with 1.8%.

Table 2A presents results on the econometric estimation of the Ricardian model (that is, the effects of climate change on household's agricultural income). The results show that Winter temperature, Summer precipitation and Winter precipitation have a significant negative association with agricultural income. However, the effects for Winter temperature square turns positive which means that Winter temperature has a u-shape relationship. This implies that as the temperature goes high, agricultural income reduces, reaches minimum and then rises. The relationship is however negative for Spring precipitation and Autumn/Fall temperature squared. The result also shows that background factors such as the use of farm inputs (for instance fertilizer and seed) and province such as Mpumalanga have a significant positive association with household's agricultural income.

Table 2B documents the observed and counterfactual average per capita income. The observed and counterfactual per capita household agricultural income are R195.4107 and R91.0405 respectively. The table also documents an average per capita income of R2602.912 for all the households in the data observed in 2014.

Results on impacts of climate change and poverty and inequality are displayed in Table 3, note that all the analyses are weighted to make the results nationally representative. The poverty headcount was estimated based on three poverty lines: food poverty line, lower-bound poverty line and upper-bound poverty line, using the observed and counterfactual distribution of income. Food poverty headcount for the agricultural households was estimated at 9.6% from the observed income distribution, and this increased to 54.1% for the counterfactual distribution. This increment

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may be attributed to the climate variability as stated earlier. Similarly, the table recorded the lower-bound poverty headcount for agricultural households at 26.6% in the observed data, which increased to about 54.1% for the counterfactual distribution of income while the upper-bound poverty headcount moved from 48.4% for the observed income to 54.2 for counterfactual distribution of income.

The table also reports poverty headcounts for all the households (that is, agricultural and non-agricultural households) using the observed and counterfactual income distribution. Results show that food poverty headcount increases from 8.1% in the observed distribution to about 10.4% in the counterfactual distribution, while the lower-bound poverty headcount increases from 15.8% in the observed data to 17.2% in the counterfactual distribution. The trend continues with the upper-bound poverty which rises from 27.2% to 27.5% from the observed to counterfactual income distribution respectively.

The statistics on the inequality also shows that inequality increases from 0.56 in the observed agricultural households to 0.70 for the counterfactual distribution and from 0.63 for all households in the observed data to 0.72 for the counterfactual income distribution.

4. Discussion

It is within the expectation that Winter temperature, Summer precipitation and Winter precipitation have a significant negative association with agricultural income. The negative association between precipitation in spring and income is consistent with Thapa and Joshi (2010). They found a negative relationship between precipitation, temperature and agriculture income. They

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documented that Autumn/Fall and Spring are the major harvesting seasons for some essential agricultural crops such as maize and rice (normally harvested in the Autumn/Fall season) and wheat (normally harvested in the Spring) that are widely cultivated. Therefore, if there is a relatively high precipitation in these seasons, it has a high tendency of causing crop damage during harvesting. However, low precipitation along with high temperature during Autumn/fall and spring is more supportive during harvesting and minimize crop damage. This also explains the significance level associated with the change analysis.

Furthermore, it is also not surprising that climate change (temperature and precipitation) is associated with household poverty. This is because, agricultural income is a component of household income and therefore, changes in climate variables that affects household agricultural income through negative impact on crop yield (Gbetibouo and Hassan, 2005) will also affect household poverty. This result reinforces parallel finding by Ahmed et al. (2009) that extreme and adverse climate events cause productivity shock that affects agricultural households and negatively influence the poverty level in Africa. In their analysis of the pathway through which household could exit poverty, Hallegatte et al. (2014) underscore that climate change and impact management can significantly drive household out of poverty and vice versa. Hallegatte et al. (2016) reported in their comprehensive outlines for poverty reduction that policy toward poverty reduction must not be implemented in isolation from policies targeted at mitigating climate change or promoting adaptation to climate change but as a reinforcement to each other. (Islam, and Winkel, 2017)

Our study finds evidence that climate change exacerbates existing inequality. This finding reinforces some of the findings in the existing literature. For instance, Skoufias (2012) notes that the adverse effect of climate change on the poor is more regressive since they are harder hit by

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climate change than those that are well-off. The study also noted, in the context of Brazil, that the gap between the poor and the prosperous regions widen even more due to climate variability over the years (Skoufias, 2012). Concerning inequality, Intergovernmental Panel on Climate Change (2014) documented that climate change has a danger of exacerbating inequality. The panel highlighted that people who are geographically and socially disadvantaged including those who are discriminated on the basis of race, gender, age, class, disability among others are more vulnerable to the adverse impact of climate change. They argued that expenditure on adaptation to climate change is incurred by people who are relatively wealthy, thus is driven by wealth than need and this expenditure further heightens existing inequality. (Georgeson et al. 2016). Furthermore, in his study, Mideksa (2010), found through the application of a computable general equilibrium model (CGE) technique on the effect of climate change on inequality in the context of Ethiopian that inequality increased by 20% due to the impact of climate change. This study supports the findings in the existing literature.

5. Conclusions

Climate change has received global attention due to its potential threats in the past, present and the future. Review of past and present studies show limited empirical studies on the subject. Particularly, the socioeconomic impact of climate change has not been extensively explored globally and in South Africa. In this paper, we investigate the relationship between climate change (precipitation and temperature), poverty and inequality using agricultural income as a transmission mechanism. Finding from the first stage analysis through the Ricardian model shows that changes in temperature and precipitation are significantly associated with changes in agriculture income. Further analysis reveals that climate change is significantly associated with higher poverty and

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ISSN 2320-9186

inequality. Based on the finding, it is recommended that promoting the adaptation capacity of poor household should be a priority as these households are highly exposed to adverse impacts of climate change.

Limitation

It is important to acknowledge some methodological limitation to this study. The estimation of counterfactual distribution of income is based on the assumption that farm practices in the future remain essentially the same as today. Also the model does not capture any change or improvement in technology that might lead to improved farm practices in the future. Furthermore, due to unavailability of complete information or data on agricultural cost, agricultural income is used in place of net income for the analysis. Notwithstanding this limitation, the study contributes significantly to quantitative approach to estimating the impact of climate change.

We also suggest future research on adaption options and their effectiveness in addressing the adverse effect of climate change. Specific attention should be given to farmers' adaptation behaviour over time and factors that determine this behaviour.

Competing interests

The authors have declared that no competing interests exist

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Ethical considerations

This article followed all ethical standards for research without direct contact with human or animal subjects

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Tables

Table 1 A Summary Statistics of climate variables

Variables	**Measurement**	**2014 Mean**	**2016 Mean**
Summer temperature	degrees Celsius	23. 0288 (1.2900)	23.0838 (1.6958)
Autumn/Fall temperature	degrees Celsius	18.5876 (2.1980)	19.4582 (1.5526)
Winter temperature	degrees Celsius	13.0022 (2.5677)	14.0003 (3.2008)
Spring temperature	degrees Celsius	17.7476 (2.6844)	18.4061 (1.7530)
Summer precipitation	millimetres	65.7546 (39.4936)	88.0389 (50.5039)
Autum/Fall precipitation	millimetres	33.9110 (44.7555)	18.8643 (14.5618)
Winter precipitation	millimetres	3.9078 (8.6461)	3.8224 (8.3214)
Spring precipitation	millimetres	32.1415 (33.1521)	46.3836 (25.4105)

standard deviations(in parenthesis)

Table 1 B Summary Statistics on household characteristics (base year, 2014)

Variables	Definition	Statistics
Agricultural Income (per capita)	Measured in South African Rand	195.4107 * (2070.516)

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Non- Agricultural Income (per capita)	Measured in South African Rand	1383.64* (2382.115)
Land use	Dummy; 1 for less than 5 ha of land use, 0 otherwise	98.24
Farm inputs used (eg fertilizer, seed)	Dummy; 1 if used Farm inputs, 0 otherwise	12.89
Male head	Dummy; 1 for Male head, 0 otherwise	34.57
Education for household head*	Years	6.09* (5.36)
Age of household head	Years	56.33* (15.237)
African	Dummy; 1 for African race, 0 otherwise	95.20
Coloured	Dummy; 1 for Coloured, 0 otherwise	3.57
Western Cape	Dummy; 1 for Western Cape, 0 otherwise	3.43
Eastern Cape	Dummy; 1 for Eastern Cape, 0 otherwise	13.85 34.02
Northern Cape	Dummy; 1 for Northern Cape, 0 otherwise	2.06
Free State	Dummy; 1 for Free State, 0 otherwise	3.43
KZN	Dummy; 1 for KZN, 0 otherwise	45.27
Northwest	Dummy; 1 for Northwest, 0 otherwise	1.78
Gauteng	Dummy; 1 for Gauteng, 0 otherwise	3.70
Mpumalanga	Dummy; 1 for Mpumalanga, 0 otherwise	6.31
Limpopo	Dummy; 1 for Limpopo, 0 otherwise	20.16
Observation1: Total household		8,970
Observation2: Agricultural household		729

Statistics with asterisk * are means and standard deviations(in parenthesis)

Table 2 Econometric estimation of Ricardian model (Effects of climate change on agricultural income)

Table 2A Econometric estimation of Ricardian model (Effects of climate change on agriculture income)

Variables	**Coefficients**
Summer temperature	-7449.740 (5375.141)

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Summer temperature^2	171.5446 (117.6951)
Autum/Fall temperature	-316.656 (1687.205)
Autumn/Fall temperature^2	-20.13532 (44.9843)
Winter temperature	2513.195** (1239.145)
Winter temperature^2	-77.5042** (37.5110)
Spring temperature	238.6129 (248.9581)
Spring temperature^2	-10.0362 (8.3474)
Summer precipitation	104.889** (52.1822)
Summer precipitation^2	-0.7139** (0.3472)
Autumn/Fall precipitation	30.6928** (15.5138)
Autumn/Fall precipitation^2	-0.2617** (0.1254)
Winter precipitation	682.0655** (316.0041)
Winter precipitation^2	-11.6307** (5.3092)
Spring precipitation	-80.0252** (39.2461)
Spring precipitation^2	0.7184** (0.3388)
Land use	-98.6864 (72.0486)
Farm inputs used	205.7913** (94.7559)
Male head	84.9796 (58.5945)
Education for household head	11.1684 (7.9576)
Age of household head	31.0712* (16.6452)
Age of household head^2	-0.2627* (0.1392)
African	-529.602 (378.9699)
Coloured	-1504.494 (1007.384)
Western Cape	4042.341* (2327.433)

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Eastern Cape	47.9360 (76.3666)
Northern Cape	1679.64 (1072.672)
Free State	2755.698 (1763.836)
KZN	-536.3371* (316.4653)
Northwest	-875.536* (518.0168)
Gauteng	2976.301* (1786.691)
Mpumalanga	2922.031** (1413.085)
Constant	69217.66 (48414.34)
R-square	0.4121
Adjusted R-square	0.3851
Prob > F	0.0000
Observation	729

*** p<0.01, ** p<0.05, * p<0.1; standard errors in parenthesis

Table 2B Total Per Capita Household Income

Variable	Mean	Std. Dev.
Agricultural households		
Per capita household agricultural income at base year (2014)	195.4107	2070.516
Per capita household agricultural income at year 2016, counterfactual	91.04049	10947.08
Per capita household non- agricultural income at base year (2014)	1383.64	2382.115
Total Per capita household income at base year (2014)	1579.051	3809.652
Total Per capita household income at year 2016, counterfactual	1474.681	11106.11
All households		
Per capita household income for the full sample (agricultural and non-agricultural households) at 2014 base year	2602.912	8012.983

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Table 3 Impact of Climate Change on Poverty and Inequality

Variables	Indexes	Observed (2014)		Counterfactual (2016)	
		Agricultural household	All household	Agricultural household	All household
Poverty headcount	Food poverty (%)	9.6	8.1	54.1	10.4
	Lower bound (%)	26.6	15.8	54.1	17.2
	Upper bound (%)	48.4	27.2	54.2	27.5
Inequality	Gini coefficients	0.56	0.63	0.70	0.72