Assessing socioeconomic vulnerability to climate change in three selected South African provinces

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Climate variability and climate change pose a threat to the livelihoods of developing countries due to their adverse impacts on infrastructure and other production systems most notable in agriculture where such impacts lead to water and food insecurities. The magnitude of the impacts of climate variability and climate change are location specific and depend on the vulnerability and sensitivity of a locale to those effects. Focused on three provinces in South Africa namely the Gauteng, Limpopo and Mpumalanga provinces, the main objective of the study is to provide empirical results on the vulnerability of the selected provinces to climate change. The study is imperative because of a perceived paucity of private and public systems preparedness to deal with the present and future adverse impacts of climate variability and climate change. The study uses a composite vulnerability index and a fixed effect regression model in the analysis of data. Results showed that the selected provinces were vulnerable to climate change but to different extents. Further, it was observed that food grains production was significantly affected by climatic stressors. The study recommends the provision of efficient irrigation facilities, drought-tolerant crops, dissemination of information on integrated pest management and provision of non-agricultural jobs.

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Abstract

Climate variability and climate change pose a threat to the livelihoods of developing countries due to their adverse impacts on infrastructure and other production systems most notable in agriculture where such impacts lead to water and food insecurities. The magnitude of the impacts of climate variability and climate change are location specific and depend on the vulnerability and sensitivity of a locale to those effects. Focused on three provinces in South Africa namely the Gauteng, Limpopo and Mpumalanga provinces, the main objective of the study is to provide empirical results on the vulnerability of the selected provinces to climate change. The study is imperative because of a perceived paucity of private and public systems preparedness to deal with the present and future adverse impacts of climate variability and climate change. The study uses a composite vulnerability index and a fixed effect regression model in the analysis of data. Results showed that the selected provinces were vulnerable to climate change but to different extents. Further, it was observed that food grains production was significantly affected by climatic stressors. The study recommends the provision of efficient irrigation facilities, drought-tolerant crops, dissemination of information on integrated pest management and provision of non-agricultural jobs.

Keywords: Vulnerability, climate change, socioeconomic indicators, composite index, agriculture.

Introduction

Climate change is here and it is manifesting as increase in the frequency and severity of extreme weather events such as droughts, floods, snow falls, heat waves etc. Climate change can be regarded as the change in state of the climate due to changes in the mean of its properties over an extended period of time usually over a 30 year period (Intergovernmental Panel on Climate Change [IPCC], 2007b). It is the alterations of the earth's atmosphere that causes changes in the climate system, such as global warming and extreme weather events (Gosain & Rao, 2003). These changes or alterations are induced by both natural and human activities. The presence of greenhouse gases (GHGs) in the atmosphere naturally warms the earth at a level suitable for habitation. However, in the last decades, it is believed that the increased concentration of GHGs in the atmosphere has caused an imbalance in the natural greenhouse effect leading to the global effect which in turn drives the climate change phenomenon (Karl & Trenberth, 2003). The major GHGs that are responsible for global warming are water vapor, carbon dioxide, methane, nitrous oxide and chlorofluorocarbons (Karl & Trenberth, 2003; IPCC, 2007b).

The impacts of climate change and vulnerability to climate change varies by region; depending on different existing environmental conditions. For example, low-lying countries of Latin America like Argentina, Mexico and Venezuela are considered the most vulnerable to extreme weather events such as rain, windstorms and hurricanes (Panda, 2009). Also, small island developing states which are spread across the Pacific, Indian and Atlantic Ocean and Caribbean Sea are reportedly highly vulnerable to climate change effects due to poor availability of resources, small but rapidly growing populations, remoteness, susceptibility to natural disasters, excessive dependence on international trade and vulnerability to global developments (Panda, 2009). The African continent is also bearing the brunt of the climate change phenomenon largely due to the fact that agriculture which is highly sensitive to climate change is the source of livelihood for majority of entire Africa's labour force (Boko et al., 2007).

Climate change impacts can result in increasing costs for human health, increasing incidence of pests, increasing costs of global economy and the earth's life support system. As result, research has largely been focusing on ways by which emissions which are enhancing global warming can be mitigated and how society can adapt to an already changed climate. The former actions fall under the climate change mitigation category of climate change management and the latter under the climate change adaptation category. Developing countries especially those in Africa have a higher need for adaptation due to their high vulnerability (Adger, Huq, Brown, Conway, & Hulme, 2003; Bryan, Deressa, Gbetibouo, & Ringler, 2009). Developing countries are the hardest hit by climate change yet they have little capacity to adapt effectively due to lack of funding, weak institutions and inability to access available funds (UNFCCC, 2007). In addition, as opined by Schipper, Cigaran, and Hedger (2008), climate change adaptation will be cost effective if “mainstreamed” into the development processes. These adjustments and changes are required at every level, from community to national and international. However, the dearth of climate data in Africa has been a serious challenge to understanding its current and future climate variability.

The paper focuses on the socioeconomic dimension of vulnerability and aims to characterise the level of vulnerability of selected South African provinces to climate change by applying a composite vulnerability index model. The paper also examines the mitigation and adaptive strategies undertaken by the farmers based on present day risk on the background of climate change informed by historical data. The structure of the paper is as follows. The next section presents the theoretical framework; discussing the concept of vulnerability to climate change impacts and dependence on socioeconomic factors. Section three presents the methodology employed in the research and section four discusses the results of the analysis. The paper concludes in section five and draws on the findings of the literature and analysis to recommend actions for policy considerations.

Theoretical framework: Vulnerability to climate change impacts

The literature on the concept of climate change vulnerability has grown enormously over the past few years leading to a number of a definitions of the concept. As a result, vulnerability assessment is based on a researcher’s choice of indicators at any given time and place. This means that climate change vulnerability is subjective and dynamic. The IPCC (2001) define vulnerability as a function of exposure, sensitivity and adaptive capacity. In the view of (Füssel, 2006), the conceptualisation of vulnerability to climate change is to consider the adaptive capacity of the vulnerable system, as this to a great extent determines its sensitivity over time. Consequently, the level of vulnerability of a country to climate change is determined by the presence of appropriate mitigation and adaptation options (Panda, 2009).

Generic determinants of vulnerability have been broadly grouped into biophysical and socioeconomic determinants. The biophysical consists of the physical, biological and ecological factors such as climatic conditions, topography, natural hazards etc. while the socioeconomic factors consists of the social, economic and cultural factor such as demography, gender, poverty, employment etc. (Preston, Yuen, & Westaway, 2011). The United Nations also identified four groups of vulnerability factors which describe the properties of a vulnerable system and are considered relevant in the context of disaster reduction. These groups are physical factors, economic factors, social factors and environmental factors (UN, 2004). Of importance to this study is social vulnerability which is defined in this study as the exposure of individuals to stress as a result of social and environmental changes directly or indirectly caused by climate variability. Change in social vulnerability from its baseline level incorporates notions of economic, institutional and political development, as well as adaptation to climatic conditions. Factors that increase exposure to climate change effects are defined as being positively correlated with vulnerability while those that increase adaptive capacity are negatively correlated with vulnerability (Füssel & Klein, 2006).

Further, various frameworks have been employed in the assessment of vulnerability. These range from the Exposure-Sensitivity-Capacity Framework, Pressure and Release Framework, Composite Index Approach, to the Driver-Pressure-State-Impact-Response Framework among others (Qiu, Li, Zhou, & Zhang, 2015). Assessment of vulnerability helps to expose climate risk areas and provide a guide to the formulation of appropriate policies and measures to mitigate or adapt to inherent climate impacts which can vary across locations, socio-economic group of persons and economic sectors. This is why vulnerability is generally defined in the context of specifics and of which the degree of sensitivity is determined by the level of dependence or exposure. Exposure is the degree to which an ecosystem is exposed to climate change impacts. The second component of vulnerability which is sensitivity deals with the extent of change or influence on a resource or population as climate variability increases. Thus, sensitivity describes the level or degree of vulnerability to climate change. It is the exposure and sensitivity of a system to climate variability that informs its adaptive strategy. Adaptive capacity is the ability of the system to adapt to changing climatic conditions and to cope with the impacts of changed climate (Qiu et al., 2015). Assessment indicators are selected to reflect the exposure, sensitivity and adaptive capacity components of vulnerability.

Furthermore, vulnerability assessments are generally done using top-down or bottom-up approaches. The top-down approach simulates and projects future impacts and usually begins with analysis of climate change and its impacts, while bottom-up approach begins with analysis of the individuals affected by climate change. Many vulnerability assessments have been done with the top-down approach (Dessai & Hulme, 2004; van Aalst, Cannon, & Burton, 2008; Wolf et al., 2013). However, it is argued that vulnerability assessments should move away from the quantification of vulnerability of places and focus more on vulnerability assessment of selected variables to specific sets of stressors. It is in this line of thought that the study is undertaken and in the context of this research, socioeconomic vulnerability to climate change in the selected provinces can be determined using certain baselines.

Although climate change impacts are global, its effects differ per locale. However, the poor in society are the most vulnerable to adverse effects of climate change more than other groups in the society. A greater percentage of the world's poor are dependent on livelihoods especially agriculture and natural resources that are highly sensitive to climate variability. It is well known that poor people with little income are unable to respond to the effects of climate change as they lack the means to buy needed pest-resistant or drought/flood-tolerant crops, access electricity, purchase farm implements etc. Consequently, increasing world population has implications for food production, employment and water usage. Increasing challenges from climate change means more effort is needed to sustain societal demand. Apparently, agriculture contributes about 14% of all GHG emissions globally making it a significant contributor to climate change (The Government of the Republic of South Africa, 2011). Yet, agriculture and forestry have huge potential for adaptation. For instance, consistent and high production of food grains boosts the adaptive capacity of a province and makes it less vulnerable. Also, forests have been identified as sustainability indicator as they act as carbon sinks to reduce atmospheric GHGs (Kadekodi, 1992; Schneider et al., 2001).

In addition, agriculture contributes about 3% to South Africa's GDP (DAFF, 2013). According to Archer, Oettle, Louw, and Tadross, (2008), agriculture in South Africa is a major source of livelihood. Field crops in South Africa occupy on average, 80 per cent of total cultivated land and contribute about 40% to the gross revenue of the total agricultural sector (Gbetibouo & Hassan, 2005). Further, irrigation agriculture is about the largest single consumer of water; it takes about 60% of the surface water used and 65% of the total water consumed in South Africa (Blignaut, Ueckermann, & Aronson, 2009). Notably, lack of water could lead to poor yield in irrigated crops (Taikan & Shinjiro, 2006; (Vörösmarty, Green, Salisbury, & Lammers, 2000). Water availability is the most important factor limiting the country's agricultural production as South Africa is regarded as semi arid due to its low mean rainfall (450mm) which occurs unevenly across the regions/provinces (Palmer & Ainslie, 2006). Evidently, the temperature in South Africa is getting hotter and drier just as the connection between crop production and rainfall has been well established (Blignaut et al., 2009). It is well known that the country is already water-stressed and is faced with a future of drying trends and weather variability. It is reported that South Africa will exceed the limits of economically viable land-based water resources by 2050 (The Government of the Republic of South Africa, 2011). In the occurrence of these events, the poor would be most affected.

On this background, the study assesses the vulnerability level of the provinces as well as the agriculture sector based on selected indicators and baselines. A baseline is the state against which change is measured (Intergovernmental Panel on Climate Change [IPCC], 2007a). Thus, temperature baseline refers to the period from which temperature increases caused by climate change are measured. The choice of the baseline is often dependent on the amount of available data and this has been seen to vary from pre-industrial temperatures to those as recent as the year 2000 (IPCC, 2007a). The baseline period for this vulnerability analysis was 1985 and 1999-2014 for want of data; the data for the climate variables span a period of 30 years (1985-2014).

Methodology

The research data was from primary and secondary sources. The primary data were collected with the aid of a structured questionnaire. While secondary data was aggregated from numerous websites which included South Africa Department of Agriculture, Forestry and Fisheries, South African Agricultural Statistics, Statistics South Africa (Stats SA), South African Weather Bureau, Population Census Report (South Africa Census 2011), Abstract of Agricultural statistics 2015, and provincial websites. The surveyed provinces were Gauteng, Mpumalanga and Limpopo. A brief description of the provinces shown in Figure 1 is as follows.

Gauteng is South Africa's smallest province yet has the largest population. About 97% of its population lives in urban areas. Its population has the highest per capita income level in the country. Gauteng covers an area of 16,548km^2 and has a population of about 12.3million (23.7% of the entire South Africa population). The Province is landlocked; it is bordered in the south by Vaal River (Free State), in the west by North West province, in the north by Limpopo and to the east by Mpumalanga. Half of the country's agro-processing companies are located in Gauteng. Mpumalanga is the second smallest province after Gauteng. It is bordered in the east by Mozambique and Swaziland and in the west by Gauteng. It borders Limpopo on the north and to the south and southwest; it borders KwaZulu-Natal and Free State respectively. Agriculture occupies more than 68% of the province area. The province also accounts for 83%

of South Africa's coal production. Limpopo province is the country's northernmost province and it shares borders with three international countries: Mozambique (at the east), Zimbabwe (to the north and northeast) and Botswana (west and north-west). It also shares borders with other provinces (Mpumalanga, Gauteng and North West). Limpopo though blessed with year-round sunshine, experiences wide climatic variations. The province due to its rich fruit and vegetable production; is regarded as the garden of South Africa.

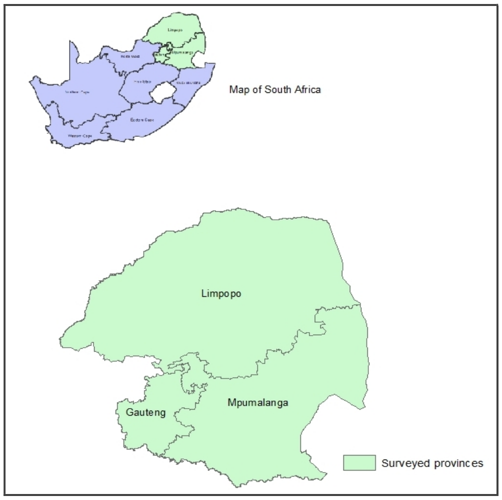

Figure 1 Study Location Map in South Africa

The socioeconomic data collected from the three provinces are relatively compared in the presupposition that where these indicators are favourably higher, then the resilience of the province to climate change would be stronger. The selected indicators are presented in Table 1 along with their expected relationship with vulnerability to climate change impacts. Provincial monthly average rainfalls were used to compute the annual sum of rainfall for the provinces. The annual average maximum and minimum temperature data were obtained from two weather stations per province. The variance in the average rainfall, maximum temperature and minimum temperature were computed for the full time period (1985-2014) and for sub-periods (1985-1999 and 2000-2014) to observe any significant differences in the climatic parameters. The standard deviation of the data series for the total quantity of major grains (maize, wheat and sorghum) produced in each province for the time period (1985-2014) was used as a measure of crop production risk. Agricultural households were measured as the proportion of households engaged in agriculture to the total population of individual province. The number of persons receiving social grants was also computed as a proportion in relation to the total population of each province. Population density was the total population of a province divided by its total land area. The irrigated area was measured as the proportion in relation to total farmland of each province while forestry area was computed as the proportion of area in relation to the total land area of a province.

Table 1. Classification of selected indicators of vulnerability

Type of Vulnerability	Indicators	Correlation to vulnerability	Component of vulnerability
Population	Population density (person/km^2)	Positive	Sensitivity
Occupational	Agricultural households (nos.)	Positive	Sensitivity
Climatic	Annual rainfall variance (mm)	Positive	Exposure
	Maximum temperature variance (^{o}C)	Positive	Exposure
	Minimum temperature variance (^{o}C)	Positive	Exposure
Agricultural	Major food grains (tonnes/ha)	Negative	Adaptive capacity
	Irrigation proportion (%)	Positive	Sensitivity
	Forest proportion (%)	Negativity	Adaptive capacity
Economic	Social grants proportion* (%)	Negative	Adaptive capacity
	Poverty (income < $1.25/day) (%)	Positive	Sensitivity

*Social grants refer to Old Age grant, War Veteran's grant, Disability grant, Grant in Aid, Child Support grant, Foster Child grant and Care Dependency grant. Source: www.sassa.gov.za; authors' elaboration.

Numerous studies (Qiu et al., 2015; Palanisami et al., 2013; Blignaut et al., 2009; Adger, 1999) have used some of the study selected indicators in vulnerability assessments. The study presupposes that the greater the number of households that are dependent on agriculture in a province, the higher the vulnerability of the people to climatic risk. In addition, the proportion of individuals earning less than US$1.25 a day was used as a proxy for poverty as the poverty line recognised globally is US$1.25 (Cobbinah, Erdiaw-Kwasie, & Amoateng, 2015). Also, population density indicates the number of persons that could be adversely affected by the impacts of climate change on food production and other activities (Gbetibouo, Ringler, & Hassan, 2010). Further *a priori* expectations are that the higher the proportion of farm land dependent on irrigation, the higher the sensitivity of the region's agriculture to climate variability; the existence of forestry can increase adaptive capacity by reducing to climatic events and providing wood fuel and food.

In the determination of the extent of vulnerability of the selected regions, the study adopted the composite vulnerability index method used by Palanisami et al. (2013). In this method, a composite index from multivariate data is computed and based on the computed index, the regions are ranked in terms of their vulnerability to climate change. The model assumes that there are *m* regions, *K* components of vulnerability; C_K number of variables in the component *K* and X_{ic} as the value of the variable c_k of the k^{th} component for the i^{th} state.

Since the values of the vulnerability indicators were in different units of measurements, they had to be standardized for uniformity. The standardised indices lie between 0 and 1. They were computed in such a way that where the observed variables are positively related to vulnerability, the standardization was computed by the formula:

$Y_{id} = (X_{id} – Min\ X_{id})/(Max\ X_{id} – Min\ X_{id})$

Whereby Y_{id} is the vulnerability index and $Min\ X_{id}$ and $Max\ X_{id}$ are the minimum and maximum of $(X_{i1}, X_{i2},....,X_{in})$ respectively. But when the values of X_{id} are negatively related to vulnerability, the standardized values were computed by the formula:

$Y_{id} = (Max\ X_{id} – X_{id})/(Max\ X_{id} – Min\ X_{id})$

The level of vulnerability of the i^{th} region is assumed to be a linear sum of the Y_{id} values for its c_k variables and is computed as follows:

$\bar{y}_{id} = \sum_{i-1}^{m} W_i Y_{ic}$

Whereby, W's ($0 < w < 1$) and $\sum_{i=1}^{n} w_i=1$) are the weights determined by:

$W_i = \frac{K}{\sqrt{var(Y_i)}}$ and $K = \left[\sum_{i=1}^{n} \frac{1}{\sqrt{var(Y_i)}}\right]^{-1}$

The weights are meant to reflect the importance of the individual variables and to ensure that any large variation in a variable does not unduly dominate the contribution of the rest of the variables (Palanisami et al., 2013). Thereafter, the vulnerability indices in line with Palanisami et al. (2013) are classified into various stages of vulnerability as follows.

< 0.20 (less vulnerable)

0.20-0.40 (moderately vulnerable)

0.40-0.60 (vulnerable)

0.60-0.80 (highly vulnerable)

> 0.80 (very highly vulnerable)

Further, the vulnerability assessment was disaggregated to determine food grain production sensitivity to climate change in the provinces through the application of a fixed effect regression model to the panel data. The total volume of grains produced was used as a proxy since the actual hectares of land planted with the crops for the period under consideration could not be obtained. The fixed effect model used assumes variation of intercept across provinces. The STATA 12.0 statistical software was used for the regression of the model specified as:

$Y_i = \alpha + \beta X_{rainfall} + \beta X_{maxtemp} + \beta X_{mintemp} + \alpha_i$

Where a_i is a composite error ($e_i + u_i$), e_i is the cross section (across province) error while u_i is the combination of cross section and time series errors.

Furthermore, on the background of vulnerability to climate change, a comprehensive list of mitigation and adaptation strategies researched from the literature was presented to farmers to indicate the strategies they have adopted in their farming to response to climate change.

Results and discussion

A summary of the aggregated data used in computing the composite index is presented in Table 2 and the descriptive statistics of the climate variables for the full time period (1985-2014) is presented in Table 3. It is seen that Mpumalanga province has received the highest amount of rainfall, although the amount of rainfall experienced in 2014 had decreased from that of the base period (1985) by 6.9%. Also, the temperature of Limpopo reduced by 0.3% in the same period.

Table 2. Summary of data used for the analysis of composite vulnerability index

Indicators	**Provinces**		
	Gauteng	**Mpumalanga**	**Limpopo**
Major grains production average (tonnes)	502.788	2403.447	279.848
Agricultural Household (%)	2.221	6.400	8.538
Social grants (%)	17.461	32.268	40.445
Income level less than $2/day (%)	2.587	4.381	3.973
Population density	655.656	51.456	41.977
Irrigated area (%)	3.545	2.597	1.528
Forestry area (%)	1.100	6.700	0.500
Annual maximum temperature variance	0.497	0.575	0.340
Annual minimum temperature variance	0.221	1.742	0.629
Annual rainfall variance	138.728	149.984	177.458

Sources: Abstract of Agricultural Statistics, 2015; South Africa Weather Services, 2015; South Africa Census, 2001, 2011; South Africa Fact Sheet on social grants.

Table 3. Descriptive statistics of pooled data for climatic stressors (1985-2014)

Variable	Province		
	Gauteng	**Mpumalanga**	**Limpopo**
Mean annual rainfall (mm)	701.806	803.990	635.408
Rainfall variance	19245.498	22495.166	31491.416
Rainfall standard deviation	138.728	149.984	177.458
Change in rainfall (%)	2.594	-6.862	2.724
Mean annual maximum temperature (^{o}C)	22.921	24.216	25.497
Maximum temperature variance	0.497	0.575	0.340
Maximum temperature standard deviation	0.705	0.758	0.583
Change in maximum temperature (%)	3.284	10.719	-0.332
Mean annual minimum temperature (^{o}C)	9.772	10.979	13.283
Minimum temperature variance	0.221	1.742	0.629
Minimum temperature standard deviation	0.471	1.320	0.793
Change in minimum temperature (%)	2.867	53.054	-3.878

Source: authors' computation (2015)

It can be observed from the results displayed in Tables 4 and 5 that there has been a decline in the mean rainfall and an increase in mean temperature in the provinces between the sub-periods. In addition, the increasing variance for the second sub-period was an indication that the climatic variables became less predictable even as they increased and decreased in absolute terms. When climate data becomes highly unpredictable and unreliable, the risk in crop production increases. The result supports the literature (Blignaut et al., 2009) that the use of water in South Africa agriculture has increased greatly since the 1970s.

Table 4. Descriptive statistics of sub-period data for climatic stressors (1985-1999)

Variable	Province		
	Gauteng	**Mpumalanga**	**Limpopo**
Mean annual rainfall (mm)	730.487	812.497	613.536
Rainfall variance	18809.922	16471.639	16625.337
Rainfall standard deviation	137.149	128.342	128.939
Change in rainfall (%)	-22.404	-4.081	-1.655
Mean annual maximum temperature (^{o}C)	22.671	23.942	25.339
Maximum temperature variance	0.429	0.570	0.275
Maximum temperature standard deviation	0.655	0.755	0.525

Change in maximum temperature (%)	3.260	3.284	-3.940
Mean annual minimum temperature (^oC)	9.760	10.425	13.501
Minimum temperature variance	0.225	2.693	0.148
Minimum temperature standard deviation	0.474	1.641	0.384
Change in minimum temperature (%)	17.462	66.987	3.679

Source: authors' computation (2015)

Table 5. Descriptive statistics of sub-period data for climatic variables (2000-2014)

Variable	**Province**		
	Gauteng	**Mpumalanga**	**Limpopo**
Mean annual rainfall (mm)	673.126	795.483	657.280
Rainfall variance	19293.091	29970.405	47581.780
Rainfall standard deviation	138.900	173.120	218.132
Change in rainfall (%)	-30.806	-37.198	-46.736
Mean annual maximum temperature (^oC)	23.170	24.490	25.655
Maximum temperature variance	0.468	0.461	0.375
Maximum temperature standard deviation	0.684	0.679	0.612
Change in maximum temperature (%)	7.246	10.142	5.032
Mean annual minimum temperature (^oC)	9.783	11.532	13.062
Minimum temperature variance	0.233	0.259	1.052
Minimum temperature standard deviation	0.483	0.509	1.026
Change in minimum temperature (%)	-6.642	-8.675	-8.856

Source: authors' computation (2015)

In Table 6, it is shown that on the average, Gauteng had 57mm less rainfall in 2000-2014 than 1985-1999, Mpumalanga also had less rainfall of about 17mm while Limpopo had 43mm more rainfall in the last decade. The probability test for variance in rainfall was significant for Limpopo province. This is an indication that the province had experienced a significant effect of climate change with regards to rainfall. Average maximum temperature changes in Gauteng and Mpumalanga provinces have been about 0.5^oC higher in 2000-2014 than in 1985-1999 while that of Limpopo was 0.3^oC higher in the same period (Table 6). However, the test of variance for minimum temperature was significant for Mpumalanga and Limpopo. The result also shows that the covariance of rainfall and maximum temperature in the second sub-period (2000-2014) in absolute terms was higher than the first sub-period.

While, the covariance of rainfall and minimum temperature were lower in the second sub-period except for Mpumalanga. The implication of these results is that, the hotter it gets, the less rainfall there was in the provinces. Thus a continuation of this trend as evidenced in this study would mean that the selected provinces stand to face increasing challenges from climate change.

Table 6. Analysis of variance and covariance of climatic stressors

Variable	Province		
	Gauteng	**Mpumalanga**	**Limpopo**
Change in annual rainfall between 1985-1999 and 2000-2014	-57.361	-17.014	43.744
Change in average maximum temperature between 1985-1999 and 2000-2014	0.499	0.548	0.316
Change in average minimum temperature between 1985-1999 and 2000-2014	0.021	1.107	-0.437
Variance test for rainfall (P (F <=f) one tail)	0.481	0.137	0.029*
Variance test for maximum temperature (P (F <=f) one tail)	0.437	0.348	0.285
Covariance for rainfall and maximum temperature (1985-1999)	-54.484	-28.893	-32.989
Covariance for rainfall and maximum temperature (2000-2014)	-72.860	-32.078	-101.122
Covariance difference (rainfall & maximum temperature)	-18.376	-3.185	-68.133
Variance test for minimum temperature (P (F <=f) one tail)	0.473	0.000**	0.000**
Covariance for rainfall and minimum temperature (1985-1999)	-3.498	-4.328	-13.298
Covariance for rainfall and minimum temperature (2000-2014)	-0.740	-22.079	-3.501
Covariance difference (rainfall & minimum temperature)	2.758	-17.751	9.792

*Significant at 5% and **significant at 1% level of testing. Source: Author's computation (2015)

Composite vulnerability index analysis

The computed vulnerability indices are presented in Table 7 and based on this result, the provinces were classified. It was observed that all the provinces given their scores were vulnerable to climate change. However, Gauteng, the most populated province and one with a higher dependence on irrigated farming has a higher vulnerability index (0.46) when compared to the others. The result supports Gbetibouo and Ringler (2009) that these provinces are facing increasing challenges from climate change. However, the vulnerability of the provinces is also dependent on available mitigation and adaptive measures.

Table 7. Composite vulnerability index and ranks

Provinces	Vulnerability index	Rank	Classification
Gauteng	0.456	1	Vulnerable
Mpumalanga	0.395	3	Moderately vulnerable
Limpopo	0.414	2	Vulnerable

Source: Author's computation (2015)

Sensitivity of major food grains to climatic stressors

The food grain panel data was first checked for multicolinearity and the results of the pairwise correlations and partial autocorrelations (Appendix 1) showed that the values were less than 0.8. This indicated the absence of multicollinearity. A unit root test was also carried to check the stationarity of the data by employing the Fisher-type unit root which uses Augmented-Dickey Fuller (ADF) method. The result (Appendix 2) showed that the data was stationary. The result of the fixed effect model is presented in Table 8. It was observed that all the coefficients of the variables had the expected positives signs and were statistically significant except for minimum temperature. The significance of the intercept implied a significant difference in the volume of grains produced across the provinces. The results agree with the literature (Mendelsohn & Dinar, 1999; Tadross et al., 2009) that rainfall and temperature play significant roles in crop production. The F test shows that all the variables put together were significant. The rho value (94.5%) indicates the variance that is due to the differences across the provinces.

Table 8. Estimates of coefficients of fixed effects model

Dependent variable: Total major food grains (tonnes)		
Variables	**Coefficients**	**P-values**
Intercept	-6104.838	0.016*
Rainfall (mm)	0.800	0.013*
Maximum temperature (^{o}C)	262.760	0.003**
Minimum temperature (^{o}C)	16.983	0.791
Sigma_u	1187.955	
Sigma_e	286.085	
Rho	0.945	
R^2	0.025	

Prob > F (3,42)	0.017
Corr (u_i, xb)	-0.165

*Significant at 5% and **significant at 1% level of testing. Source: Author's computation (2015)

In order to determine the appropriateness of the model, the Hausman's specification test was used and it is observed from Table 9 that the null hypothesis of no cross-sectional effect is rejected. Thus, the fixed effect model is deemed appropriate since the differences in the coefficients are systemic (provincial effects). The rejection of the null hypothesis reinforces the high value of rho.

Table 9. Hausman specification test

Variables	Fixed effects coefficients (b)	Random effects coefficients (B)	Difference (b-B)
Rainfall (mm)	0.800	2.567	-1.767
Maximum temperature (^{o}C)	262.760	291.778	-29.018
Minimum temperature (^{o}C)	16.983	-195.805	212.788

Test: H_0: difference in coefficients not systemic

Chi2 (3) = (b-B) '[(v_b-v_B) ^ (-1)] (b-B) = 177.83

Prob > chi2 = 0.000

An additional regression was done for the individual grains and the result presented in Table 10 shows that a unit increase in rainfall and minimum temperature had positive and significant effects on the volume of maize across the provinces. On the other hand, both maximum and minimum temperature increase have had statistically significant negative effects on the production of wheat. One implication of this result is that future decline in rainfall would have adverse effects on maize production. The result also agrees with Gbetibouo et al. (2010) that increasing climate would have negative effects on wheat production but positive impacts on maize. Thus, there is a need to adopt appropriate measures to ensure food grain production is not threatened.

Table 10. Estimates of coefficients for individual food grain

Dependent variable:	**Maize**		**Wheat**		**Sorghum**	
Variable	**Coefficients**	**P-values**	**Coefficients**	**P-values**	**Coefficients**	**P-values**
Intercept	-6962.538	0.009**	687.806	0.008**	169.895	0.131
Rainfall	0.836	0.001**	-0.026	0.408	-0.009	0.509

Max temp	285.403	0.585	-16.958	0.049*	-5.684	0.134
Min temp	34.428	0.006**	-17.656	0.010**	0.212	0.942
Sigma_e	1199.529		88.282		28.890	
Sigma_u	281.594		29.249		13.004	
Rho	0.948		0.901		0.832	
R^2	0.012		0.350		0.047	
Corr (u_i, xb)	-0.261		-0.950		-0.489	

*Significant at 5% and **significant at 1% level of testing

Mitigation and adaptive strategies adopted by farmers

The previous results (Tables 4-6) showed that there have been changes in the average rainfall and temperature of the provinces. Both Mpumalanga and Limpopo provinces had significant changes in their minimum temperature. Limpopo also had significant changes in its rainfall. Due to changes in rainfall and temperature, most farmers have resorted to diverse range of coping strategies as will be seen later. The socioeconomic characteristics of the farmers were examined and the result presented in Table 11 indicates that the majority of the farmers were in the middle age (35-50 years) and mostly had less than 5 years farming experience. More so, most of them did not have access to any form of formal credit.

Table 11. Socioeconomic characteristics of sample farmers

Variable	Mean	Group	Frequency (%)
Age (years)	46.533	20-35 years	40 (16.53)
		35-50	113 (46.69)
		50-65	70 (28.93)
		>65	19 (7.85)
Education (categorical)		Below matric	119 (49.79)
		Matric level	90 (37.66)
		Tertiary and above	30 (12.55)
Gender (dummy)		Female	122 (49.80)
		Male	123 (50.20)
Household size (Nos.)	5.388		
Farm size (hectares)	5.967	<2hec	75 (31.25)
		2 5	127 (52.92)
		5-10	22 (9.17)
		>10	16 (6.67)
Farming experience (years)	8.975	1-5 years	93 (39.24)

	6-10	83 (35.02)
	11-15	22 (9.28)
	16-20	25 (10.52)
	>20	14 (5.91)
Land ownership (categorical)	Rented	31 (12.81)
	Self-owned	173 (71.49)
	Communal and traditional holding	38 (15.70)
Access to formal credit (dummy)	Yes	67 (28.27)
	No	170 (71.73)
Other sources of income aside farm	Yes	108 (46.96)
	No	122 (53.04)

Source: Field survey (2015)

It was gathered that the farmers have faced and were experiencing significant changes in weather pattern in the three provinces and as such, farmers were adopting various strategies to cope with the changed climate. The strategies which are presented in Table 12 were ranked based on their popularity among the farmers. It was observed that most of the farmers were planting drought resistant varieties and changing the time of planting and irrigation among others to reduce the adverse effects of climate change on their production.

Table 12. Percentage analysis of mitigation and adaption strategies adopted by farmers

Strategies	**Frequency**	**percentage**
Planted drought-resistant varieties of crops	134	54.69
Changed times of farm operations	113	46.12
Applied integrated pest management	111	45.31
Applied crop diversification and relocation of crop	100	40.82
Increased access to agricultural extension services	62	25.31
Cultivated improved and early maturing crops	60	24.49
Total number of respondents	245	

Source: Field survey (2015)

Conclusion

The paper had set out to evaluate the vulnerability status of three selected provinces of South Africa given some important socioeconomic indicators. In achieving the aim of the study, it examined the changes in the rainfall and temperature values over a 30 year period ane proceeded further to investigate the effect of the climatic stressors on the quantity of major food grains produced in the provinces. The findings from the ANOVA and regression analysis showed that there has been a significant change in the climate parameters and there has been a significant effect of the climate parameters on the level of grain production. In addition, it was observed that in response to changed climate-related events, farmers were engaging in various strategies to mitigate the effect of the changing climate on their production. On the basis of the result findings (declining rainfall and increasing temperature), the paper therefore recommends that farmers' access to improved quality seeds that are drought-tolerant should be enhanced, farmers should be provided with water storage and efficient irrigation facilities to cope with shortage of rainfall and there should be expansion of agricultural extension services to educate farmers on changing planting times and adopting integrated pest management as dictated by the changing climate.

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Appendix 1

Table A. Pairwise correlation

Variable	Total grains	Rain	Maximum temperature	Minimum temperature
Total grains	1.000			
Rainfall	0.369	1.000		
Maximum temperature	-0.004	-0.304	1.000	
Minimum temperature	-0.066	-0.038	0.710	1.000

Table B. Partial and semi partial correlations of food grains with regressors

Variable	Partial correlation	Semipartial correlation	Partial correlation^2	Semipartial correlation^2	Significance value
Rainfall	0.426	0.424	0.181	0.180	0.003
Maximum temperature	0.239	0.222	0.057	0.049	0.110
Minimum temperature	-0.214	-0.198	0.046	0.039	0.153

Appendix 2

Table C. Unit root test (Fisher-type test)

Variable	Statistics	P-values
Total grains	-4.786	0.000
Rainfall	-4.930	0.000
Maximum temperature	-4.188	0.000
Minimum temperature	-4.044	0.000