Food Security
https://doi.org/10.1007/s12571-020-01023-0

ORIGINAL PAPER

Integrated assessment of climate change impacts on crop productivity and income of commercial maize farms in northeast South Africa

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Received: 4 June 2019 / Accepted: 5 March 2020

Abstract

Agriculture in South Africa sustains about 70% of the region's population for food, income and employment, playing an important role for food security and the local economy. The focus of the study was the commercial maize farms of the Free State Province given their importance in the National economy. The Regional Integrated Assessment (phase I) was implemented to assess climate change and adaptation that links climate, crops, economic data and tools developed by the Agricultural Model Intercomparison and Improvement Project (AgMIP). In this context, the "system" is defined as a whole of agronomic and socio-economic factors. Within that framework three core questions were being evaluated: (i) Impacts of climate change under current system; (ii) Impacts of climate change under future system; (iii) The role of adaptation under climate change and the future system. Maize production will decrease between 10% to 16% as a result of projected climate impacts. Also, current agricultural production systems are negatively affected by climate change with an increase in poverty rates between 2% to 3%. The projected adoption of the adapted technology would result in positive increased net returns and a decrease in poverty rate of between 12% and 22%. The results of this study show that implementing adaptation measures and other strategies as indicated by the local stakeholders will have positive impacts on the agricultural production systems and can contribute to support and inform climate change policy decision making such as the development of National Adaptation Plans.

Keywords Integrated assessment · Climate change · Crop modelling · Adaptation · Climate models · Economic modelling

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s12571-020-01023-0) contains supplementary material, which is available to authorized users.

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1 Introduction

Agriculture in South Africa sustains about 70% of the region's population for food, income and employment, playing an important role for food security and the local economy (Southern Africa Development Community – SADC 2013). The country has a unique feature having both well-developed commercial farming systems and smallholder subsistence-based production systems. The former, are characterized by large economic investments on their farms, modern crop management techniques with high inputs (e.g. nitrogen), and extensive use of labour, and market-oriented production. The latter are characterized by low use of inputs and minimal labour usage, with production oriented to local markets and self-consumption. Given the importance of the commercial farms in the economy of South Africa for achieving self-sustaining maize production, this study evaluates the likely impacts of climate change and adaptation on commercial maize farms of the Bethlehem region. We implemented the Regional Integrated Assessment (RIA), a new approach to climate change and adaptation assessment that links climate, crops, livestock and economic data and tools developed by the Agricultural Model Intercomparison and Improvement Project (AgMIP; www.agmip.org, Antle et al. 2014). Further details of the protocols and the appended technical documents are freely available online (www.agmip.org and http://agmip-ie.alterra.wur.nl/). The AgMIP-RIA assessment has been applied to numerous case studies in different regions of the South East Asia and Sub Saharan Africa (Freduah et al. 2019).

Most of the agricultural production in South Africa is rainfed which means that farmers rely on rainfall to grow crops and produce marketable yields, and climate projections suggest that there will be serious threats to agricultural production affecting both commercial and smallholder farmers (Tadross et al. 2005; Schulze 2007; Davis 2011; Engelbrecht et al. 2013). Climate projections indicate that South Africa will likely experience moderate decreases of rainfall and higher inter-annual variability, increased probability of drought events, increase in minimum and maximum temperatures, and a decrease of water availability due to the changes in land-use towards industrial and urban usage (Meadows 2006; Ruane et al. 2015a). A recent study by Zampieri et al. (2019) confirmed that global maize production will be negatively impacted by a 1.5C increase in temperature as early as the next decade. Commercial farmers are vulnerable to climate change due to the size of their operations and the capital invested. Negative impacts of climate change can be offset by changes in crop management (e.g. planting dates, crop rotations), development of new genotypes, investment in infrastructure and agricultural policies (Claessens et al. 2012; Antle et al. 2017).

The impacts of climate change on crop production and the effects of changing management practices have been simulated using crop simulation models (CSMs) (Challinor and Wheeler 2008). CSMs integrate the temporal and multiple interactions of stresses on daily crop growth under different environmental and management conditions (Jones et al. 2003). However, these commodity-specific types of assessments are not enough to properly assess the impacts of climate change on farmers livelihoods. Thus, an approach that informs policy decision-making and support long-term planning and investment on adaptation strategies is needed.

Different approaches have been proposed to address assessments of climate change impacts on agriculture. AgMIP has developed the RIA, a protocol-based approach to link climate, crop, and economic data and modelling tools to assess the impacts of climate change and adaptation strategies on agricultural systems (Rosenzweig and Hillel 2015). This trans-disciplinary and system-based approach for evaluating regional impacts on agricultural systems captures climatic, biophysical, and socio-economic interactions using rigorously documented protocols and methodologies (see Antle et al. 2014, for details). A key feature of the approach is the stakeholder engagement to identify the research priorities by identifying key indicators, co-design adaptation strategies that are locally relevant, and co-developed future development pathways and scenarios.

In this study we use the AgMIP RIA to evaluate the maize-based commercial agricultural systems in the north eastern part of the Free State Province of South Africa under current and future climate, bio-physical and socio-economic conditions using data and analyses of the first phase (Phase I) of the AgMIP's RIA. The approach used in this study allowed capturing the high degree of variability in each region and obtain distributional outcomes, such as the proportion of farms that are vulnerable to climate change (i.e. farms at risk of losing due to climate change) and changes in farm net returns and poverty rate, defined here as the Foster-Greer-Thorbecke (FGT) headcount poverty index.

Since its inception the RIA protocol has evolved from its original form and the application of the new protocol (Phase II) is documented elsewhere (http://agmip-ie.alterra.wur.nl/). In this context, the "system" is defined as a whole of agronomic and socio-economic factors; and for this study the focus is Maize system. Within that framework three core questions were being evaluated:

1. Impacts of climate change under current system: The impacts of climate change are evaluated with the assumption that the production system does not change from its current state under current biophysical and socio-economic conditions. While this type of analysis can provide some insights into potential impacts, its relevance is limited because of the use of current socio-economic conditions to quantify impacts. This question also relates to "Business as usual";

2. Impacts of climate change under future system: The impacts of climate change on a projected production system (biophysical and socio-economic) in a future world is quantified. This type of analysis is more relevant to understanding climate impacts and thus the potential benefits of adaptation, but is more challenging because all of the relevant variables affecting the maize systems must be projected into the future;
3. The role of adaptation under climate change and the future system: the question addresses the design of adaptation options for the future production systems, the degree to which they would be likely to be adopted, and the economic, environmental, and social outcomes that would be associated with their use.

Therefore, the objective of this study was to use the AgMIP RIA approach to study the sensitivity of the current and future agricultural production system to projected climate change.

2 Materials and methods

2.1 Site description

The Bethlehem district was in the north eastern part of the Free State Province, Republic of South Africa (28° 57’ S; 25° 53′ E; 1200 to 1640 m a.s.l.). The district was selected for a case study because it was representative of large-scale commercial farming systems (Fig. 1).

To perform the integrated impact assessment at regional level, detailed descriptions of the maize-farming practices were required for both crop and economic models’ parameterization. A household survey that provided information on each field was not available, so data were obtained from secondary sources. Field boundaries and crop classification were obtained from Ferreira et al. (2006) and Durand (2016). This method identified 5000 fields planted to maize of which 400 were randomly selected for crop model simulations. Crop management inputs as to planting date, plant population, and row widths were obtained from objective yield surveys (Durand 2016). Information for the economic model was derived from enterprise budgets (Grain South Africa - SA 2012) and the census of commercial agriculture 2002 (Statistics SA 2005).

2.2 Climate

For this study daily weather data for the 1980–2010 period were used. This time frame has been used in many other crop modelling simulation studies (Asseng et al. 2013; Rosenzweig and Hillel 2015). The daily minimum and maximum temperatures and rainfall were extracted from the Climate System Analysis Group, University of Cape Town records. Data gap filling and quality control was accomplished using the AgMERRA approach (Ruane et al. 2015a, 2015b). Solar radiation was calculated following the approach of Allen et al. (1998). Homogenous climate areas were defined, and farm-specific daily climate datasets were computed by geographical bias correction (relying on the WorldClim dataset obtained from www.worldclim.org).

Changes from the current climate (1980–2010) to near-future (2010–2040), mid-century (2040–2070) and end-of-century (2070–2100) were computed. Twenty global climate models (GCMs) were used to compute twenty delta changes in monthly temperatures and monthly rainfalls, hence producing 20 future weather scenarios per baseline. For this study, RCP 8.5 was selected (The RCPs described the forcing effects of atmospheric greenhouse gases to 2100), representing increases in energy of 8.5 W m^{-2} for 2100. The RCPs are a greenhouse gas concentration trajectory which are consistent with the ranges of possible changes of greenhouse gas emissions. For example, the RCP 4.5 assume the greenhouse gas emission to peak around 2040 and then decline, while the RCP 8.5 projects rises through the twenty-first century. Additional details of the RCPs can be found on the IPCC website regarding the methodology and additional detailed references (IPCC 2019). A corresponding CO_2 level of 571 ppm was used when simulating crop response for the mid-century. A CO_2 level of 360 ppm was used when simulating the baseline period (1980–2010).

2.3 Soil

Soil physical property data (e.g. clay, silt, sand, bulk density, organic carbon) were derived for each field using the land-type database (Agricultural Research Council 2006). Soil hydraulic property data (e.g. lower limit, drain upper limit, saturation) were derived using specific pedo-transfer functions derived for South African soils (Smithers and Schulze 1995). Land-type in this case was defined as an area with uniform micro-climate, typical terrain morphology, and characteristic soil-distribution pattern in the landscape. The original land-type database with a spatial reference to polygons was modified to a spatial land-type database based on a 90 m STRM (The NASA Shuttle Radar Topographic Mission) digital elevation model (DEM). The soil properties required for crop modelling were derived using the identified soil series suitable for maize production within each terrain unit. The soil properties for each field were first calculated for each terrain unit to determine the weighted averages of the soil properties. Then, the soil properties for each field (400 fields in total) were calculated based on the percentage representation of each terrain unit within a field using zonal statistics. This resulted in each field having a unique soil description.

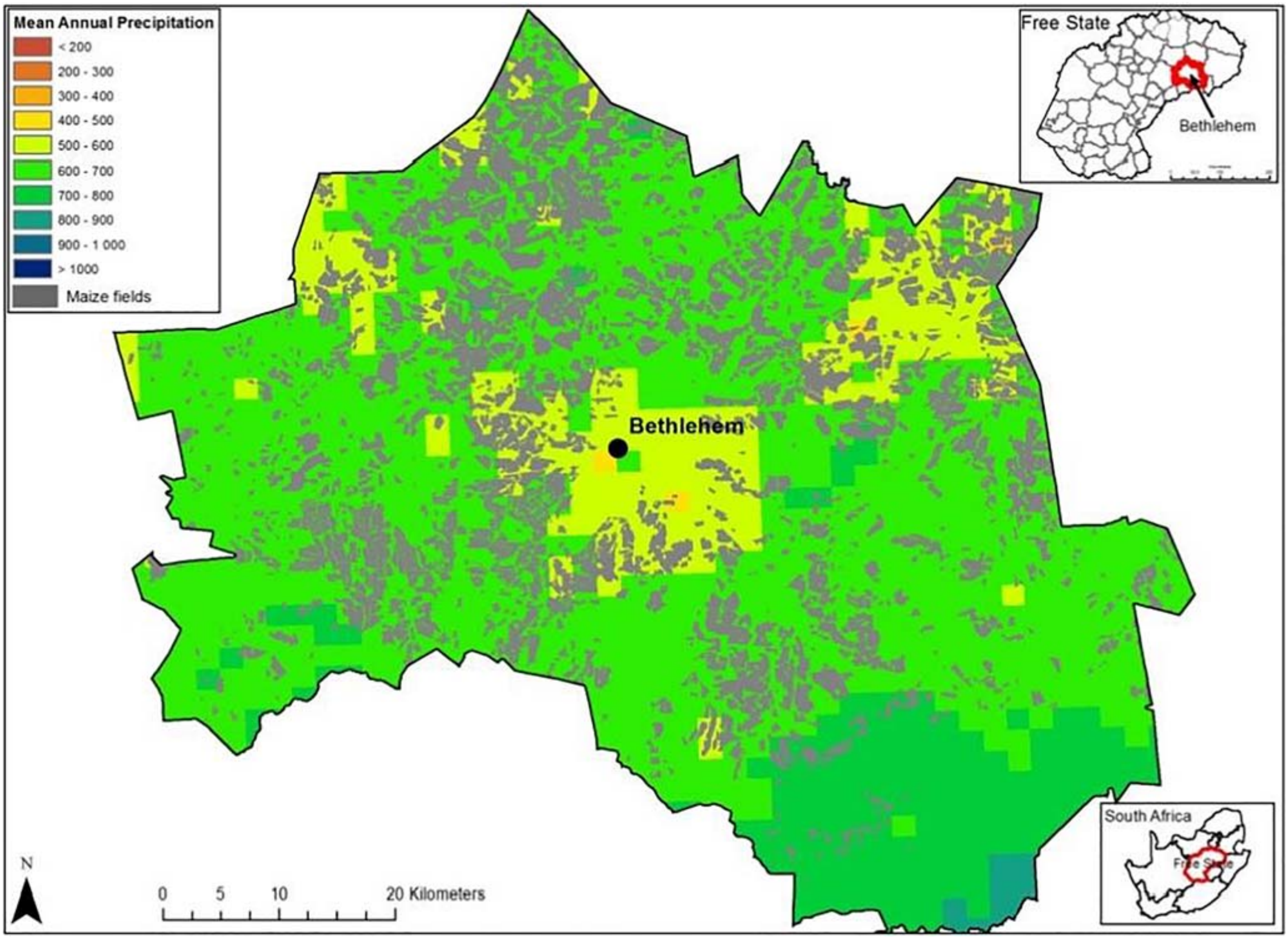

Fig. 1 Map of the Bethlehem district (Free State, South Africa). Mean annual rainfall is represented by the colors, while the grey areas are the commercial maize fields

2.4 *Crop modelling*

To establish crop management input for crop modelling, the Free State province was divided into two rainfall zones, i.e., above and below 500 mm rainfall per annum. 1542 samples obtained from objective yield surveying over a 6-year period (2008–2013) were used to calculate the proportion of fields with certain row widths, planting dates and plant populations for maize in each of the two zones. The same proportion was used to assign the management strategies to all the fields within the Free State and subsequently the Bethlehem district using the "Sample Features" command of Geospatial Modelling Environment (Beyer 2012). The planting window was between 30 September and 30 December, row width between 75 and 280 cm, plant population 0.5–5.5 plants per m^2, and fertilizer 20–90 kg N ha^{-1}. Fertilization was based on the average modelled 50-year yield potential of each field using the 50-year Quaternary Catchments Database (QCDB) climate data (Schulze et al. 2007). The rule of 15 kg Nitrogen (N) per hectare for each ton of grain produced was used (Maize Information Guide 2014). A summary of the crop management is shown in Supplemental Material Tab. S1. On this basis, N fertilization applications ranged from 20 to 90 kg N ha^{-1}.

Two crop simulation models, Decision Support System for Agrotechnology Transfer (DSSAT v4.5; Hoogenboom et al. 2012) and Agricultural Production Simulation Model (APSIM v7.5; Keating et al. 2003) were used. The two crop models' input were soil physical and hydraulic properties, daily weather data, crop genetic characteristics, and agronomic management such as row width, planting population, fertilizer application, and planting date.

The maize models were calibrated using data from a range of field experiments by Du Toit (1996), Du Toit et al. (1994a, b, c, 1997, 1998), Du Toit and Prinsloo (2000). These datasets represent a range of different locations, varieties, plant densities, planting dates, row widths and years. The genetic coefficients for maize in APSIM v7.4 were derived using the experimental work of Ncube et al. (2007, 2009) and Dimes and Du Toit (2009). Although PAN6479 is not a new hybrid, this medium-maturing maize hybrid was selected because it was commonly grown during the baseline simulation period.

The resulting genetic coefficients for the maize genotypes used are reported in Supp. Material Tab. S2 for DSSAT and APSIM.

Common modelling practices suggest that once calibrated a model should be evaluated on an independent dataset to test its ability to reproduce a given trend or a yield level. In this study, the crop models were evaluated using district-level observed data for large-scale farmers for 18 years of recorded yields (1981–1999). A measure of models' accuracy was the root mean square error (RMSE) between observed and simulated yields was calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=l}(y_i - y_i)^2} \quad (1)$$

where y_i are the measurements, y_i the simulations, and n is the number of comparisons.

Crop yields were simulated for each field for the current period (1980–2009) and the future (2040–2070) using climate scenarios from the 20 GCMs described in Supp. Material Tab. S3.

2.5 Designing future development pathways

Agriculture is a complex system where biophysical, economic, policy and social factors interact to determine farmers' production each season. These factors will likely change under future policies, biophysical, and socio-economic conditions. To assess the likely impacts of climate change and adaptation strategies under future conditions, defined scenarios that characterize and define likely future conditions were developed. These scenarios, called Representative Agricultural Pathways (RAPs) were developed in a series of meetings between scientists and stakeholders. A RAPs defined as storylines with qualitative and quantitative information that describe possible trends of key drivers into the future was developed for South Africa. Information on drivers such as future farm and household size, costs of production, crop management, prices and policy can be translated into economic and crop model parameters (Claessens et al. 2012; Valdivia et al. 2012). RAPs are consistent with new scenario concepts being developed by the international climate modeling and impact assessment communities with inputs from stakeholders. Methods developed by Valdivia et al. (2015) within the AgMIP approach were used to develop a "*Business as Usual*" RAP for South Africa. Meetings with stakeholders were held between 2012 and 2014 with the participation of farmers, farmer-unions' representatives, economists, and agriculture experts. Interaction with stakeholders continued after the meetings on an individual basis to refine specific aspects of the RAPs (Table S3). Their feedback was useful in gaining information for developing the RAP narratives and to gain information about current conditions and on future trends of the Free State Region (and South Africa) in terms of future governmental agricultural policy implementation and its impact on the agricultural sector.

The RAP developed was consistent with the '*Business as Usual*' trend and the final narrative for South Africa was described as *"South Africa will follow a more positive economic development pathway in line with the National Development Plan; Vision 2030 (National Planning Commission 2012) characterized by higher rates of economic growth, increased agricultural technology development and use, and increased access to productive commercial agricultural land. Increased investments in implementing agricultural and land reform policies provide a positive environment for increased agricultural production of commodities such as maize, improved economic performance and associated reductions in poverty enhance social cohesion and facilitate investments in commercial agriculture production such as maize production (20% increase in variable costs; 10% increase in output price; 15% decrease in farm size and 5% increase in productivity growth due to technology change)"*.

The key drivers identified by the team of stakeholders and scientists is presented in Fig. 2 where the arrows represent the direction of change (increase, decrease, no change) and the magnitude of that change (from small to large change). The results of the RAPs process showed future conditions with increased soil degradation that might be compensated by the use of improved varieties, and higher fertilizer use. These drivers were used as input to crop simulation models. Other aspects like the change in farm size, input and output prices and off-farm income were used as input to the economic model.

2.6 Co-design of future adaptation strategies

Engagement with stakeholders was also needed to co-design possible adaptation strategies that were of interest to stakeholders and that could be tested using our modeling approach for this region. The resulting adaptation package included:

i) an increase of 30% of fertilizer: such increase was justified by the feedback received by the stakeholders and was based on the assumption that current N management system is inefficient in commercial maize farming. Such mismanagement is causing low NUE and non-optimal application amounts and timing (Nel and Bloem 2006; Van Biljon et al. 2008). An increase with N amount with a better strategic and tactic management is therefore planned. In the near-future, precision agriculture could help to optimize the agronomic management so that crops will be responsive to the an additional 30%.

ii) a change of maize variety from a medium to a long season: The switch to long season variety is justified

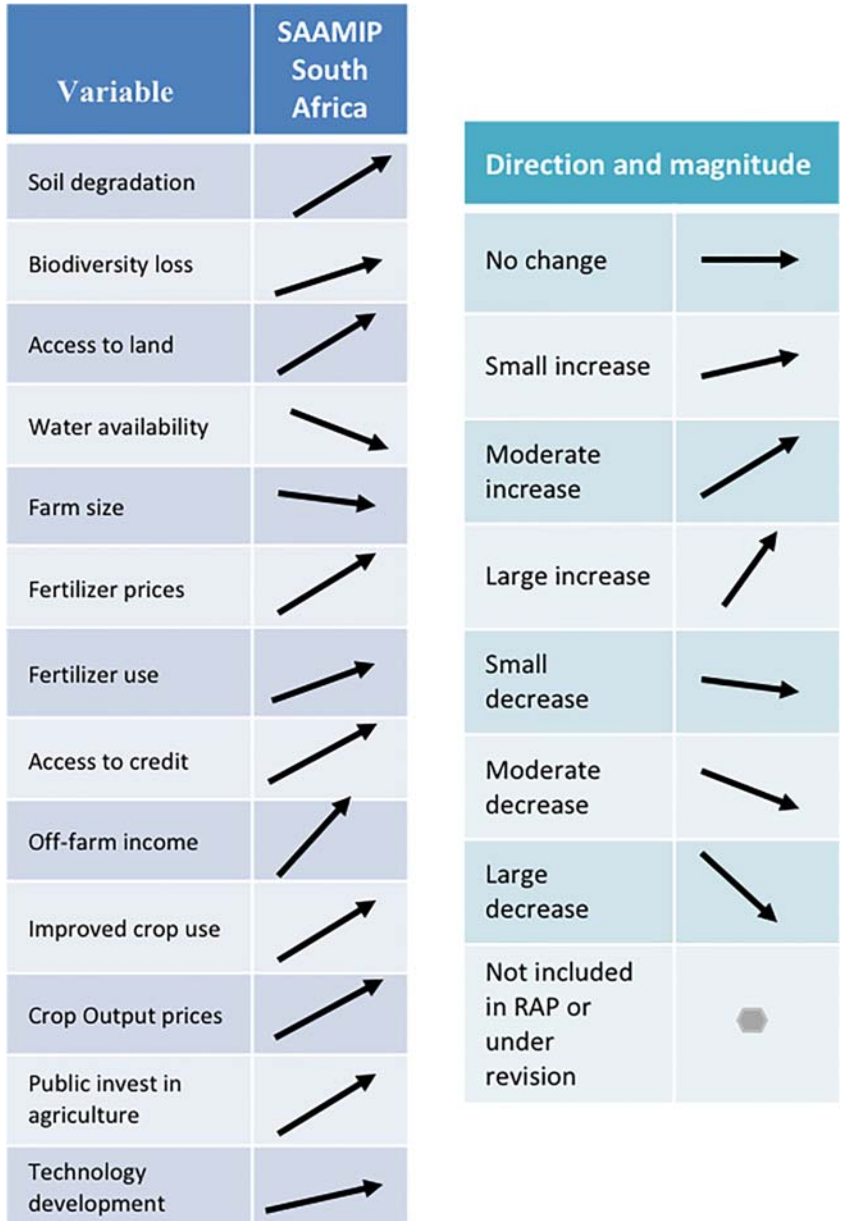

Fig. 2 Representative Agricultural Pathways for South Africa maize-based systems in Bethlehem. Key drivers identified by stakeholders and scientists

by the projected temperature trends. An increase in growing season temperature means that crop development will be accelerated causing less accumulated biomass and lower yields. To offset such negative impacts of temperature on crop development a longer season cultivar is considered as part of the adaptation package.

2.7 *Economic modelling*

The Trade-Off Analysis Model for Multi-Dimensional Impact Assessment (TOA-MD; Antle 2011; Antle et al. 2014) was used to evaluate the impacts climate change on farm income and poverty rates and assessing sustainable alternatives in mixed farming systems for the commercial farmers. The socio-economic data for the model input were obtained from the Census of agriculture 2002 and 2007 (Statistics SA 2005, 2010), the 2011 census (Statistics SA 2012a) and enterprise budgets from Grain South Africa (Statistics SA 2012b). The enterprise budgets were used to calculate net returns (mean and standard deviation), and variable cost for maize, based on each individual field's production (Table S4).

TOA-MD provides the capability to go beyond the analysis of averaged or aggregated data, by representing the distributions of economic, environmental and social outcomes in heterogeneous populations of farm households. In the case of climate impact assessment, the TOA-MD model can be used to show how the distributions of outcomes are affected by climate and by adaptations farmers adopt to offset the impacts of climate change. In the TOA-MD model, farmers are presented with a simple binary choice: they can continue operating their farming system with a current or base production system 1, or they can switch to an alternative (e.g. 'adapted') system 2. The model simulates the proportion of farms that would adopt the new or alternative system, as well as the impacts of the new system by simulating impact indicators such as poverty rates, farm net returns, per-capita income and others. The TOA-MD simulates impacts that are statistically associated with adoption, using the standard statistical framework for econometric policy evaluation in which economic "agents" – in our context, farms – self-select into "treatment", i.e., choose to adopt or not adopt. The model can be used to estimate the so-called "treatment effects" or the impacts associated with technology adoption. Thus, the model is able to estimate the proportion of farms that would adopt the alternative technology (i.e. those who would self-select). Likewise, the TOA-MD is used to assess climate impacts by using a simple analogy to technology adoption. Farms cannot choose whether to have climate change or not, but if farms had such a choice, those that would choose to "adopt" climate change are those who would gain from it; farms that would prefer not to "adopt" climate change are those who would lose from it. The impacts of climate change estimated by the TOA-MD model are the "treatment effects" of climate change.

In this case the TOA-MD estimates the proportion of farms that would gain and the proportion that would lose from it. In this context, we define vulnerability as the proportion of farms that are at risk of losing from climate change. The phenomenon of losers and gainers from climate change can be explained (at least in part) by the heterogeneity in the conditions in which the farms operate, such as soils, water resources, topography, climate, the farm household's socio-economic characteristics, and the broader economic, institutional and policy setting. For a detailed description of the TOA-MD model readers are advised to check the work of Antle et al. 2017.

The change in revenue of the crops under current conditions and not simulated was derived from the Free State Province Census of commercial agriculture (2007) and by interacting with different stakeholders (reported in Table S3) that have direct knowledge of the market (Table S5).

3 Results

3.1 *Climate*

Historical daily average temperatures, rainfall and projected changes from baseline (1980–2010) to the mid-century 2050s (2040–2070; RCP8.5 and 20 GCMs) are shown in Fig. 3. Mean monthly temperatures (black line and stars, Fig. 3a) were projected to increase consistently with little variability across the GCMs (boxplots, Fig. 3a). The projected mean annual temperature ("*ann*" in the right box of Fig. 3a) showed an increase of mean temperature between 2.8 and 4.8 °C increase respect to the baseline (11.05 °C). Overall, the GCMs boxplots did not show high variability, with the range of projected winter mean temperature (defined as the June, July, and August) being the smallest, suggesting a greater confidence in projection for that season. While for the mean temperature the GCMs agreed in terms of the direction (warming), for the rainfall (Fig. 3b) there was higher uncertainty in both the amount and the direction of change, especially during summer (December, January, and February).

Figure 4 shows the mean growing season temperature and rainfall distribution of the 20 GCMs respect to the baseline. Among the 20 GCMs, 5 of them were selected to give a representation of full range of temperature changes. Including all GCMs x RCPs x Crop models x adaptation packages x RAPs would lead to an impractical number of combinations for full integrated assessment. The 5 GCMs chosen for this study were the CCSM4; GFDL_ESM2, HADGEM2_ES, MIROC5, MPI_ESM as documented in Ruane et al. (2015a, 2015b). In addition, the GCMs subset was selected to be consistent cross all the different case-study of the AgMIP-RIA so larger patterns of change on a continental scale can be detected. However, this meant that not all possible climate change types were included in all locations. These 5 GCMs were chosen to have higher resolutions, prominence in the literature, participation in CMIP activities, and an adequate performance in the monsoon regions. It is also important to note that the selected GCMs included a range of climate sensitivities (2.4–4.6 °C equilibrium global mean warming for a doubling of CO_2; Flato et al. 2013).

3.2 *Crop modelling*

The models were evaluated for their ability of simulating phenology (anthesis and maturity) and grain yield. The average simulated maize grain yield for commercial farmers using baseline weather data (1980–2010) was 3155 kg ha^{-1} with a CV of 49% between farms. The RMSE for yield was 1360 and 748 kg ha^{-1} for DSSAT and APSIM, respectively.

Figure 5 showed variation of simulated maize yield due to the spatial variability of tested fields and management practices combinations. The mean simulated yield with DSSAT was about 1000 kg ha^{-1} higher than the one simulated by APSIM over the 30 years period. The shape of the yield distribution was different between the two models with APSIM showing less variability between the 400 simulated fields.

Simulated grain yield using projected climate from the 5 GCMs declined for both crop models, with the APSIM model estimating lower yields compared with DSSAT (Fig. 6). The variability and the simulated yield by APSIM (boxplots) were

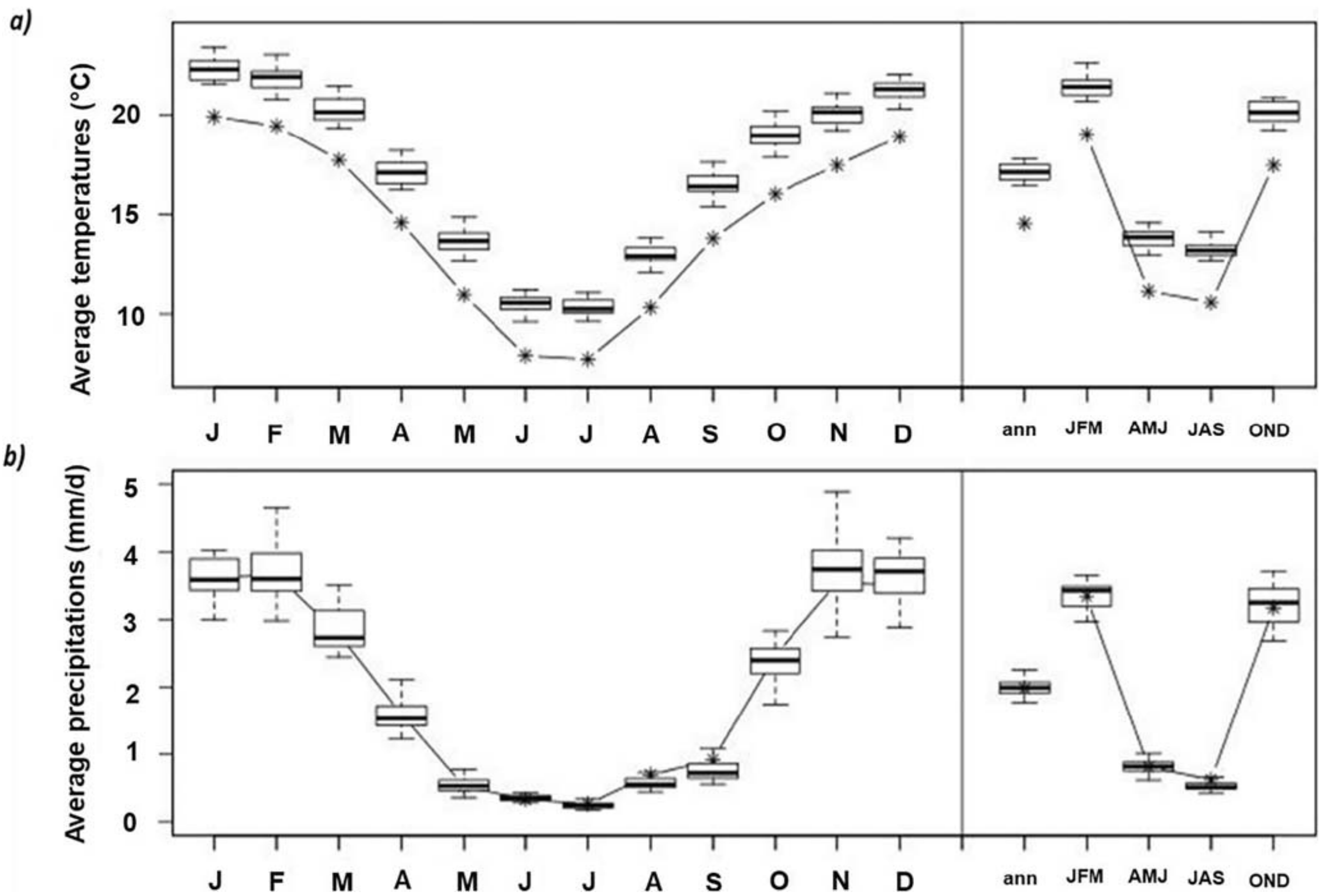

Fig. 3 Current (black line and stars) and projected (box-and-whiskers) monthly and seasonal mean temperature (*a*) and precipitation (*b*), projected by 20 CMIP5 global climate models for Bethlehem, Free State, South Africa in the 2050s under RCP8.5. ann = Annual; JFM = January, February, March; AMJ = April, May, June; JAS = July, August, September; OND = October, November, December

lower among the 5 GCMs, especially for the GDFL, HADGEM2, and MPI_ESM (Fig. 6). However, the overall simulated median yield decline respect to the baseline was estimated to be about 10% and 16% with DSSAT and APSIM, respectively.

The simulated impacts of climate change and the benefit of agronomic adaptations (included in the adaptation package) for the simulated maize yields were summarized in Fig. 6 for future systems under projected climate. Simulated maize yields without adaptation was decreased between 2425 to 2375 kg ha^{-1} due to the changes in climate, while adaptations increased simulated yields for both baseline and projected effects of climate.

3.3 *Economic modelling*

3.3.1 Current farming systems

The likely impacts of climate change to the current production system to climate change is shown in Table 1. Overall, the current system was negatively affected by the projected changes in climate under all the 5 GCMs. Grain yield decreased between 9 and 28% while net returns decreased between 10 and 28%. The proportion of farms that are vulnerable to loss due to climate change is high and ranges between 62% to 80%. Poverty rates increased between 2 and 5%, however it is important to note that current poverty rates among the commercial maize farms is already very low at about 8%. The current poverty rate for South Africa was estimated considering the different definitions of poverty lines that are officially used in the country and represented here as of 2014 statistics: (a) Food poverty line: R305 per capita per month, i.e. R3660 per capita per year; (b) Lower-bound poverty line: R416 per capita per month, i.e., R4992 per capita per year; and (c) Upper-bound poverty line: R577 per capita per month i.e., R6924 per capita per year. For this study we used the Lower-bound poverty line (R4992 per capita per year). This includes the food poverty line (R305) plus the average amount derived from non-food items of households whose total expenditure is equal to the poverty line (Statistics SA 2012). Commercial farms that make large

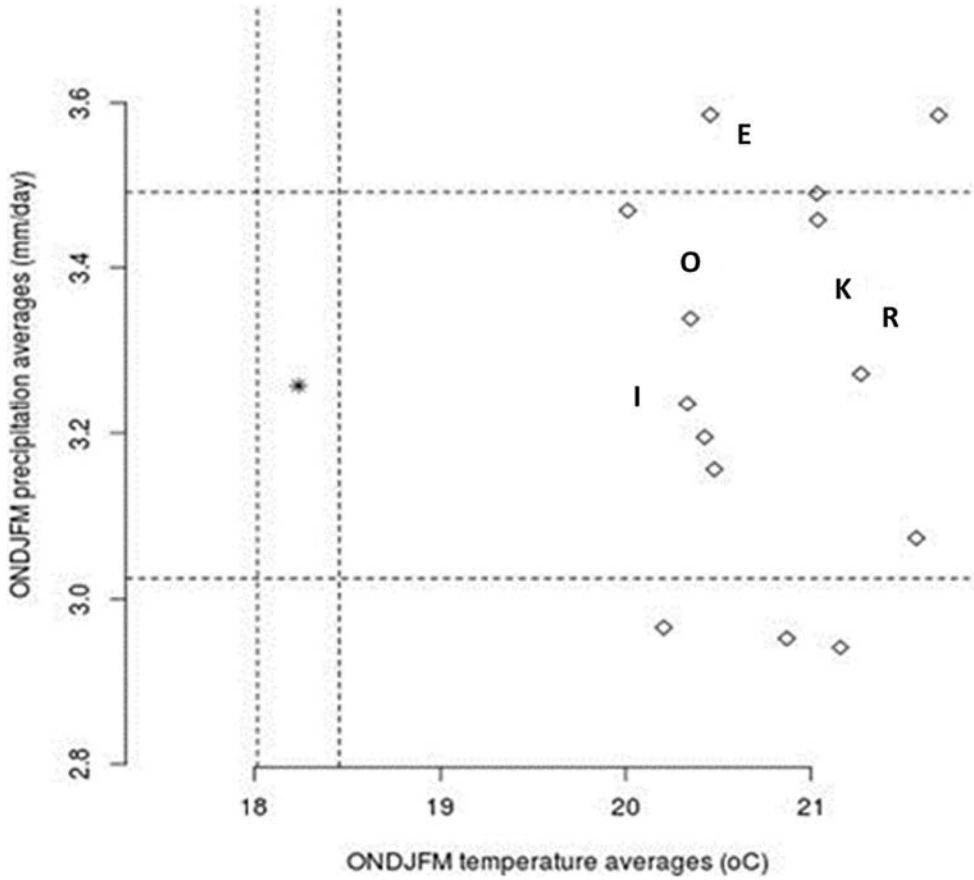

Fig. 4 Mean (October to March) temperature and precipitation projected by 20 CMIP5 global climate models (diamonds) and the 5 GCMs selected for this study (letters E, I, K, O and R) for Bethlehem, South Africa in the 2050s under the high-emissions RCP8.5 scenario. The black star represents the current conditions. The vertical and horizontal dashed lines indicate the boundaries of statistical significant deviation expected from the 31 years baseline period for temperature and rainfall, vertically and horizontally respectively

investments on capital, inputs, and manage the farms intensively are at risk of larger loses.

3.3.2 Future farming systems

The results suggest that if this region in South Africa follows the Business As Usual pathway, represented by the conditions set by the RAPs, climate change will have a negative impact on commercial maize farms. The proportion of vulnerable farms (i.e. farms at risk of losing due to climate change) ranges between 53 and 80%. Mean farm net returns decrease between 8% and 30% (Table 2). These negative impacts are mostly due to the decline in crop yields due to climate change. Increase in output prices and other future conditions (e.g, increase in off-

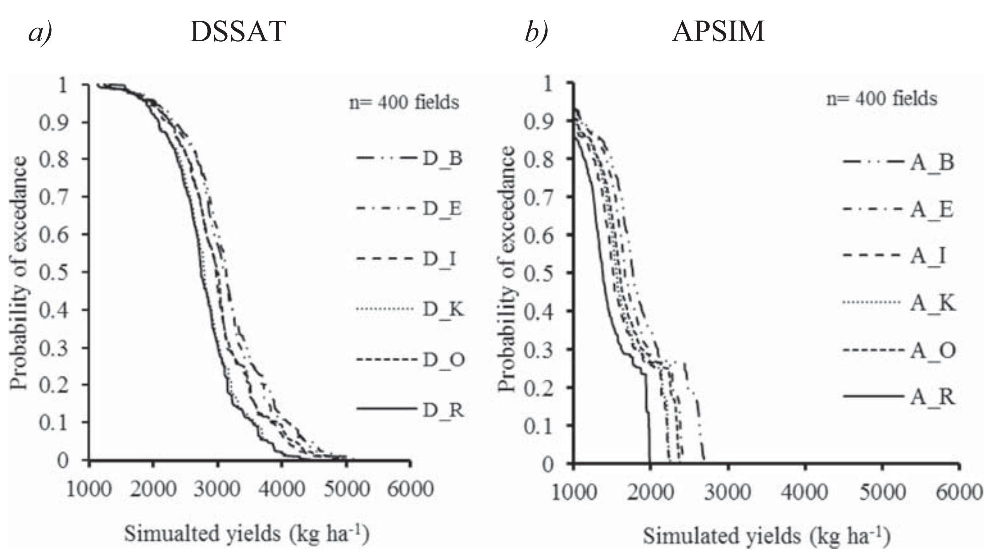

Fig. 5 Probability of exceedance plots showing the effects of climate simulated maize yields using (*a*) DSSAT (D_) and (*b*) APSIM (A_). Each line represents the simulated yields for 400 fields and averaged over the 30-years period, for the baseline (1980–2010; B) and the five GCMs CCSM4 (E); GFDL_ESM2 (I); HADGEM2_ES (K); MIROC5 (O); and MPI_ESM (R)

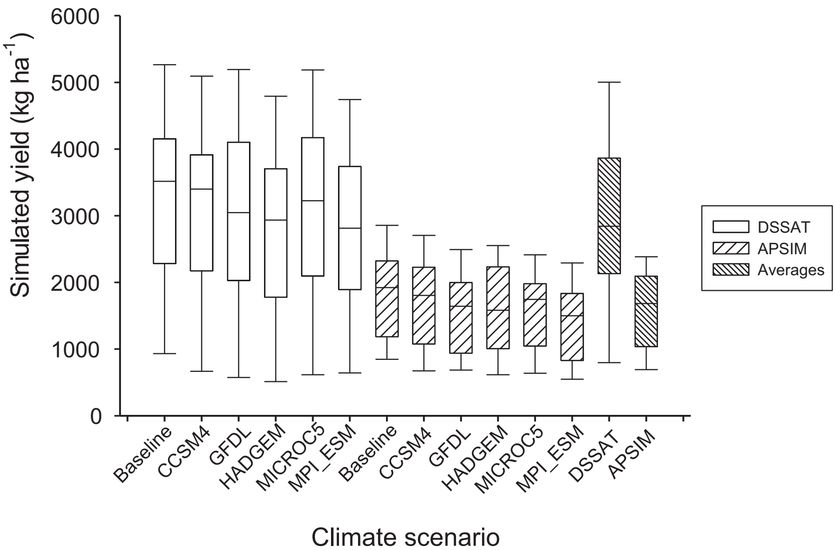

Fig. 6 Interannual variability of the simulated maize yield in Bethlehem district for DSSAT and APSIM and the 5 chosen global climate models (CCSM4, GFDL_ESM2, HADGEM2_ES, MIROC5, and MPI_ESM). For each boxplot the horizontal lines from the top to the bottom represent the 90th, 75th, 25th, and 10th percentiles, the middle line represents the median value

farm income), combined with the increased production costs (e.g. increased use of fertilizer) resulted on low farm net returns and are not enough to offset the bio-physical effects of climate change on yields. This suggests that assessing possible adaptation strategies that can offset the effects of climate change is important. In particular, as Fig. 2 showed, the different stakeholders when designing the RAP indicated that the off-farm income will be a major component.

The adaptation analysis projected that between 58% and 65% of the farmers would adopt the proposed package. This would increase average farm net returns in the population increase between 20% and 26%. This was due to the increased maize yields (between 13% and 21%). Therefore, poverty rates decrease about 20% across the different scenarios (Tab. 3).

4 Discussion

The combination of stakeholders' interactions and the scientific methods for using their information as input to crop and economic models allowed the assessment of the likely impacts of climate change and adaptation of commercial maize-based farm systems in South Africa. Our results show that climate change will likely have negative impacts on these maize farming systems. Poverty rate in this population of farms (i.e. commercial farms) is already very low and the estimated impacts are small. The reason for this is that we have used the head count ratio, which estimates the proportion of people that live below the poverty line. If the changes in net farm returns or per-capita income are not enough to bring more people below the poverty line, then the poverty rate change is small. A better indicator that could be used in future analysis is the FGT poverty gap that measures the intensity of poverty.

Another point worth highlighting from our results is that although mostly negative, not everybody loses from climate change and this is, in part, explained by the bio-physical and socio-economic heterogeneity that characterizes the farming system. Under both current and future conditions, there is a proportion of the farms that may actually gain from climate change. This has important implications for policy making, the design of adaptations or policies need to be tailored to those who actually would benefit from them. Blanket interventions have the risk of failure (e.g. low adoption or early dis-adoption).

One of the key features of this study is the interaction between stakeholders and scientists since the beginning of the project for the development of the RAPs and the co-design of the adaptation package. This was achieved through a series of multi stakeholder interactions with different institutions (Table S3). Some of the stakeholder gave feedbacks on the current crop management systems in each region that helped considering the regional variability of crop management practices, while others provided useful feedback for understanding on how governments' future policies agenda will affect the agricultural sector. The RAP developed with the stakeholders was positive and based on the government "*National Development Plan 2030*" (NPC 2012), but it was only one of the plausible trends that could happen in the next 20 years. Development of other plausible futures, for example one RAP with better development conditions (i.e. better future socio-economic and technological conditions) will increase the value of this approach but were not considered in this phase of the project.

Changes in farm income and the poverty rates in population indicated that in addition to climate there are other factors that could contribute to offset the negative effects of climate change like increased income from other sources external to agriculture, better future prices, and improvement in

Table 1 Sensitivity of current agricultural production systems to climate change simulated with the TOA-MD model using the inputs from APSIM (AP) and DSSAT (DS) from 5 GCMs, the CCSM4 (E); GFDL_ESM2 (I); HADGEM2_ES (K); MIROC5 (O); and MPI_ESM (R)

Stratum 1	CCMS4		GFDL		HadGEM_2ES		MIROC-5		MPI-ESM	
	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT
observed mean yield (maize) (kg/ha)*	2993.23	2993.23	2993.23	2993.23	2993.23	2993.23	2993.23	2993.23	2993.23	2993.23
mean yield change (crop name) (%)	−13.00	−9.00	−17.00	−12.00	−21.00	−14.00	−11.00	−11.00	−28.00	−18.00
losers (%)	66.58	61.83	71.51	62.91	73.59	66.52	66.03	63.10	79.38	71.05
gains (% mean net returns)	21.32	22.51	20.32	22.23	19.99	21.36	21.45	22.18	19.38	20.47
Proportion of farms vulnerable to CC (% mean net returns)	−31.47	−29.60	−34.01	−29.99	−35.38	−31.47	−31.22	−30.06	−40.58	−33.85
observed net returns without climate change (ZAR/farm)	2,881,311.24	2,881,311.24	2,881,311.24	2,881,311.24	2,881,311.24	2,881,311.24	2,881,311.24	2,881,311.24	2,881,311.24	2,881,311.24
observed net returns with climate change (ZAR/farm)	2,482,975.69	2,601,617.68	2,347,360.77	2,575,362.88	2,283,284.44	2,484,110.85	2497,347.65	2,570,617.17	2,068,279.76	2,359,244.76
observed per-capita income without climate change (ZAR/Person/Year)	870,556.73	870,556.73	870,556.73	870,556.73	870,556.73	870,556.73	870,556.73	870,556.73	870,556.73	870,556.73
observed per-capita income with climate change (ZAR/Person/Year)	750,807.11	786,473.86	710,037.87	778,581.01	690,774.93	751,148.36	755,127.68	777,154.33	626,139.14	713,610.50
observed poverty rate without climate change (%)	8.34	8.34	8.34	8.34	8.34	8.34	8.34	8.34	8.34	8.34
observed poverty rate with climate change (%)	8.70	8.53	8.73	8.49	8.72	8.55	8.72	8.50	8.78	8.55

* *Normalized;* ** Defined as: (mean relative yield-1)*100; *** *Poverty line: Lower-bound poverty line (R416)* per capita *per month or (R4992)* per capita *per year*

Table 2 The impact of climate change on future agricultural production systems simulated with the TOA-MD model using the inputs from APSIM (AP) and DSSAT (DS) from 5 GCMs, the CCSM4 (E); GFDL_ESM2 (I); HADGEM2_ES (K); MIROC5 (O); and MPI_ESM (R)

Stratum 1	CCMS4		GFDL		HadGEM_2ES		MIROC-5		MPI-ESM	
	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT
projected mean yield (maize) (kg/ha)	3666.53	3666.53	3666.53	3666.53	3666.53	3666.53	3666.53	3666.53	3666.53	3666.53
mean yield change (crop name) (%)	−13.00	−9.00	−17.00	−12.00	−21.00	−14.00	−11.00	−11.00	−28.00	−18.00
Proportion of farms vulnerable to CC (%)	63.62	53.39	69.27	59.35	72.75	62.92	62.73	55.62	79.55	70.79
gains (% mean net returns)	22.56	25.64	21.11	23.67	20.41	22.71	22.85	24.86	19.46	21.08
losses (% mean net returns)	−30.96	−27.72	−33.33	−29.36	−35.31	−30.64	−30.69	−28.28	−40.96	−34.62
projected net returns without climate change (ZAR/farm)	2,898,826.22	2,898,826.22	2,898,826.22	2,898,826.22	2,898,826.22	2,898,826.22	2,898,826.22	2,898,826.22	2,898,826.22	2,898,826.22
projected net returns with climate change (ZAR/farm)	2,565,665.47	2,816,378.84	2,417,598.75	2,672,571.67	2,315,342.85	2,583,905.28	2,587,580.92	2762,675.76	2,069,613.21	2,366,794.95
projected per-capita income without climate change (ZAR/Person/Year)	834,739.58	834,739.58	834,739.58	834,739.58	834,739.58	834,739.58	834,739.58	834,739.58	834,739.58	834,739.58
projected per-capita income with climate change (ZAR/Person/Year)	739,352.48	811,134.11	696,959.57	769,960.74	667,682.73	744,574.71	745,627.08	795,758.40	597,327.99	682,413.96
projected poverty rate without climate change (%)	8.66	8.66	8.66	8.66	8.66	8.66	8.66	8.66	8.66	8.66
projected poverty rate with climate change (%)	9.39	8.71	9.51	8.69	9.48	8.71	9.52	8.72	9.68	8.68

* *Normalized;* ** Defined as: (mean relative yield-1)*100; *** *Poverty line: Lower-bound poverty line (R416)* per capita *per month or (R4992)* per capita *per year*

Table 3 The potential benefits of climate-change adaptations to future agricultural production systems simulated with the TOA-MD model using the inputs from APSIM (AP) and DSSAT (DS) from 5 GCMs, the CCSM4 (E); GFDL_ESM2 (I); HADGEM2_ES (K); MIROC5 (O); and MPI_ESM (R)

Stratum 1	CCMS4		GFDL		HadGEM_2ES		MIROC-5		MPI-ESM	
	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT
projected mean yield without adaptation (maize) (kg/ha)	2762.03	2925.47	2659.75	2829.31	2497.29	2782.05	2877.94	2863.81	2273.20	2616.54
mean yield change (crop name) (%)	19.54	21.98	15.66	14.77	20.25	15.12	21.35	19.10	15.28	13.41
% adoption rate	58.61	62.60	62.97	63.13	64.74	59.93	65.20	61.32	64.70	59.94
projected net returns without adaptation (ZAR/farm)	2,474,622.29	2,753,956.63	2,327,600.18	2,614,888.53	2,230,247.11	2,526,918.81	2,490,454.65	2,700,968.70	1,988,000.32	2,317,336.91
projected net returns with adaptation (ZAR/farm)	2,963,755.79	3,344,977.46	2,869,721.11	3,187,673.49	2,786,646.85	3,015,733.89	3,126,643.63	3,252,426.62	2,480,080.32	2,764,024.93
projected per-capita income without adaptation (ZAR/Person/Year)	713,285.95	793,262.03	671,192.12	753,445.51	643,319.01	728,258.94	717,818.91	778,091.08	573,961.45	668,253.65
projected per-capita income with adaptation (ZAR/Person/Year)	853,329.53	962,476.92	826,406.50	917,439.30	802,621.55	868,211.35	899,965.87	935,978.74	714,848.64	796,144.68
projected poverty rate without adaptation (%)	9.03	8.45	9.15	8.44	9.12	8.45	9.16	8.45	9.31	8.43
projected poverty rate with adaptation (%)	7.19	6.59	7.24	6.59	7.23	6.57	7.28	6.58	7.28	6.54

* *Normalized;* ** Defined as: (mean relative yield-1)*100; *** *Poverty line: Lower-bound poverty line (R416)* per capita *per month or (R4992)* per capita *per year*

technology. However, these may not be enough in farming systems where losses from climate change can be large. Furthermore, the interaction of projected changes in climate with natural and socio-economic factors such as increasing rainfall variability, decreasing soil fertility, reduction of farm sizes due to land reform will exacerbate the impacts on crop production systems in Bethlehem area. Our results demonstrate the need for designing adaptation strategies to face the impacts of climate change. Our study focuses on an adaptation package based on two agronomic practices: increased use of mineral fertilizer and change in crop variety. However, there was consensus among stakeholders and scientists at the end of the project that a more comprehensive adaptation package that includes policies aimed to facilitate the implementation of the adaptation package is needed. Hence, increased government support for improving agricultural technologies and extension will contribute to increase and maintain adoption of the adaptation package.

The choice of the 5 GCM based on the approach described above meant that some peculiar climate patterns (e.g. decrease in precipitation) was not well represented (Zampieri et al. 2019). In addition, Galmarini et al. (2019) concluded how the delta-method approach might not be the best way to represent the climate models outputs. In fact, the next phase of this AgMIP-RIA activity (Phase II) saw the modification of the GCM selection in terms of model selection and the inclusion of extreme characteristics in the scenario generation process using an approach described in detail in Ruane and McDermid (2017).

The evaluation of the two crop models showed some discrepancies between the simulated and observed values (in terms of RMSE). This is caused by the approach used for calibration and evaluation. The former was done using detailed experimental data. The latter was done at district level using observed data aggregated over a large area. Therefore, the calibration and evaluation datasets have a different spatial scale. At district level (evaluation dataset) the models were run with a range and a combination of management factors, soil and weather to depict the regional variability of the 400 fields simulated. As a result, the combination of these two factors contributed to such discrepancies during the evaluation. Maize crop models have been systematically compared against observed data under different environmental conditions (Bassu et al. 2014). Among 23 maize simulation model it was found that the simulated yield and phenology were reduced by higher air temperature due to the acceleration in development and the increase of CO_2 concentration could not offset it. Their simulated response was in line with the Free-Air CO_2 enrichment (FACE) experiments on maize (Long et al. 2006). However, two recent studies using the same maize models compared their ability to simulate yield and water use against other FACE with treatments of water stress and against evapotranspiration data (ET) from an 8-years long experiment (Durand et al. 2018; Kimball et al. 2019). In both cases there was a significant divergence in simulated yield and water use, and the main source of variability was in the simulation of potential evapotranspiration. However, all these three studies concluded that the models' ensemble was able to reproduce the mean experimental changes. This was confirmed on wheat by Asseng et al. (2013) and Martre et al. (2014) where ensemble with two models were also compared. In this study the two crop models used (DSSAT and APSIM) were part of that original study and their simulated yield variability is in line to the one reported in the abovementioned study. In addition, each model was run with 5 different GCM which also contributed in increasing the variability among models. The overall higher values of DSSAT with respect to APSIM can be the result of the way the two models simulate the water balance and the biomass accumulation, and the way water deficit impacts expansive growth process (Saseendran et al. 2008).

5 Conclusions

Climate projections for South Africa indicated an increase in temperature and an increased variability in rainfall, increasing the food insecurity in the region. The results from the crop models and the five different climate scenarios show that current maize production in Bethlehem will be reduced by 10% to 16% due to climate change. Also, the economic modelling results showed that current agricultural production systems are negatively affected by climate change with decreased net returns per hectare and per capita, and an increase in poverty rates between 2% to 3%. Future agricultural production systems are likely to be negatively impacted by climate change if no adaptation measures are applied. The proportion of farms vulnerable to climate change under current and future conditions is high, between 53 to 80%. The projected adoption of the adapted technology would result in increased net returns and a decrease in poverty rate of between 12% and 22%. Overall, the results of this study show that implementing adaptation measures and other strategies like the ones included in the RAP and suggested by the stakeholders will have positive impacts on the agricultural production systems and would offset the negative impacts of climate change. This proof-of-concept study demonstrated how the integration between scientific fields together with the stakeholder engagement gave many "*reality-checks*" in terms of technology trends, crop management practices, and policy The approach used, can contribute to support and inform climate change policy decision making such as the development of National Adaptation Plans. Future work should be expanded to different regions, agricultural systems (e.g. with a focus on smallholder farmers), and time-frame for aiding future planning of the agricultural sector in South Africa.

Acknowledgments Research reported in this article was possible owing to generous financial support from the UK Department for International Development, project GB-1-202108 to AgMIP, the Agricultural Model Intercomparison and Improvement Project. Fund disbursement on behalf of AgMIP was facilitated by USDA-ARS, Columbia University, and ICRISAT. Results reported reflect the views of the authors. We also thank the two anonymous reviewers and the Editor for the feedback that helped to improve the manuscript. Funding support was provided by the NASA Earth Sciences Division for the GISS Climate Impacts Group (281945.02.80.01.13).

Compliance with ethical standards

Conflict of interest The authors declared that they have no conflict of interest.

References

Agricultural Research Council and Land Type Survey Staff (2006) Land types of South Africa: Digital map (1:250 000 scale) and soil inventory datasets, Agricultural Research Council, Institute for Soil, Climate and Water, Pretoria.

Allen RG, Perreira LS, Raes D, Smith M (1998) Crop evapotranspiration: Guidelines for computing crop require-ments. Irrigation and drainage paper no. 56, FAO, Rome requirements.

Antle, J.M., Homann-Kee Tui, S., Descheemaeker, K., Masikate, M., Valdivia, R. (2017) Using AgMIP regional integrated assessment methods to evaluate climate impact, adaptation, vulnerability and resilience in agricultural systems. In: Lipper L, Zilberman D, McCarthy N, Asfaw S, Branca G (eds) Climate smart agriculture - building resilience to climate change. Springer.

Antle, J.M., Stoorvogel, J., & Valdivia, R. (2014). New parsimonious simulation methods and tools to assess future food and environmental security of farm populations. *Philosophical Transactions of the Royal Society B, 369*. https://doi.org/10.1098/rstb.2012.0280.

Antle, J. M. (2011). Parsimonious multi-dimensional impact assessment. *American Journal of Agricultural Economics, 93*, 1292–1311.

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rotter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L. A., et al. (2013). Uncertainty in simulating wheat yields under climate change. *Nature Climate Change, 3*, 827–832.

Bassu, S., Brisson, N., Durand, J. L., Boote, K., Lizaso, J., Jones, J. W., Rosenzweig, C., Ruane, A. C., et al. (2014). How do various maize crop models vary in their responses to climate change factors? *Global change biology*. https://doi.org/10.1111/gcb.12520.

Beyer, H.L. (2012) Geospatial Modelling Environment (Version 0.7.3.0) available at: http://www.spatialecology.com/gme Accessed 20 March 2019.

Challinor, A. J., & Wheeler, T. R. (2008). Crop yield reduction in the tropics under climate change: Process and uncertainties. *Agric Forest Meteorol, 148*, 343–356.

Claessens, L., Antle, J. M., Stoorvogel, J. J., Valdivia, R. O., Thornton, P. K., & Herrero, M. (2012). A method for evaluating climate change adaptation strategies for small-scale farmers using survey, experimental and modeled data. *Agricultural Systems, 111*, 85–95.

Davis, C.L. (2011). Climate Risk and Vulnerability: A Handbook for Southern Africa. Available at: https://www.csir.co.za. Accessed on 20 Mar 2019.

Dimes, J.P., Du Toit P., (2009) Quantifying water productivity in rainfed cropping systems in Limpopo Province, South Africa. In: Humphreys E, Bayot RS (eds) Increasing the Productivity and Sustainability of Rainfed Cropping Systems of Poor Smallholder Farmers. Proceedings CGIAR Challenge Program on Water and Food International Workshop on Rainfed Cropping Systems, Tamale, Ghana, 22–25 September, 2008, The CGIAR challenge program on water and food, Colombo, Sri Lanka.

Durand, J. L., Delusca, K., Boote, K., Lizaso, J., Manderscheid, R., Weigel, H. J., Ruane, A. C., Rosenzweig, C., et al. (2018). How accurately do maize cropmodels simulate the interactions of atmospheric CO2 concentration levels with limited water supply on water use and yield? *European Journal of Agronomy, 100*, 67–75.

Du Toit AS (1996) The quantification of the compensation ability of the maize plant, PhD thesis, Department of Agronomy, Faculty of Agriculture, University of the Free State, South Africa.

Du Toit, A. S., Booysen, J., & Human, J. J. (1994a). Evaluation and calibration of CERES-maize 1. Non-linear regression to determine genetic parameters. *S Afr J Plant Soil, 11*, 96–100.

Du Toit, A. S., Booysen, J., & Human, J. J. (1994b). Evaluation and calibration of CERES-maize 2. Phenology prediction values. *S Afr J Plant Soil, 11*, 121–125.

Du Toit, A. S., Booysen, J., & Human, J. J. (1994c). Evaluation and calibration of CERES-maize 3. Row widths for the western Highveld. *S Afr J Plant Soil, 11*, 153–158.

Du Toit, A. S., Booysen, J., & Human, J. J. (1997). Use of linear regression and correlation in the evaluation of CERES3 (maize). *S Afr J Plant Soil, 14*, 177–182.

Du Toit, A. S., Booysen, J., & Human, J. J. (1998). Calibration of CERES3 (maize) to improve silking date prediction values for South Africa. *S Afr J Plant Soil, 15*, 61–66.

Du Toit AS, Prinsloo M.A. (2000) Incorporating prolificacy into CERES-maize prediction of kernel number. Physiology and Modelling kernel set in maize CSSA special publication no. 29, crop science Society of America and American Society of agronomy, Madison, USA.

Durand, W. (2016) Crop yield forecast data for South Africa. In: S. Pasetto (ed.) crop yield forecasting: Methodological and institutional aspects. Food and agriculture Organization of the United Nations (FAO), Rome, Italy.

Engelbrecht, C. J., Engelbrecht, F. A., & Dyson, L. (2013). High-resolution model-projected changes in mid-tropospheric closed-lows and extreme rainfall events over southern Africa. *International Journal of Climatology, 33*, 173–187.

Ferreira, S.L., Newby, T., and du Preez E. (2006) Use of remote sensing in support of crop area estimates in South Africa. SPRS archives XXXVI-8/W48 workshop proceedings: Remote sensing support to crop yield forecast and area estimates, pp. 51-52.

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S.C., et al. (2013). Evaluation of Climate Models. In Stocker TF, Qin D, Plattner GK, Tignor M, Allen SK, Boschung J, Nauels A, XiaY, Bex V, Midgley PM (eds.), Climate Change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

Freduah, B., MacCarthy, D.S., Adam, M., Ly, M., Ruane, A.C., Timpong-Jones, E.C., Traore, P.S., Boote, K., Porter, C., Adiku, S.G.K. (2019) Sensitivity of maize yield in smallholder systems to climate scenarios in semi-arid regions of West Africa: Accounting for variability in farm management practices. J. Agronomy (in revision).

Galmarini, S., Cannon, A. J., Ceglar, A., Christensen, O. B., & Noblet-ducoudré, N. De. (2019). Adjusting climate model bias for agricultural impact assessment: How to cut the mustard. Climate Services, 13(June 2018), 65–69.

Grain South Africa - S.A.(2012) Market Reports. Available at: www.grainsa.co.za. Accessed 30 Mar 2019.

Hoogenboom, G., Jones, J.W., Wilkens, P.W., Porter, C.H., Boote, K.J., Hunt, L.A., Singh, U., Lizaso, JL, White JW, Uryasev O, Royce FS, Ogoshi R, Gijsman AJ, Tsuji GY, Koo J (2012) Decision support system for Agrotechnology transfer (DSSAT) version 4.5. University of Hawaii, Honolulu, Hawaii.

Intergovernmental Panel on Climate Change – IPCC (2019) Representative Concentration Pathways (RCPs). https://sedac.ciesin.columbia.edu/ddc/ar5_scenario_process/RCPs.html (Verified 25 Oct 2019).

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., & Ritchie, J. T. (2003). The DSSAT cropping system model. *European Journal of Agronomy, 18*, 235–265.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., & Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy, 18*, 267–288.

Kimball, B.A. et al. (2019). Simulation of maize evapotranspiration: An inter-comparison among 29 maize models. *Agricultural and Forest Meteorology, 271*, 264–284.

Long, S. P., Ainsworth, E. A., Leakey, A. D. B., Nosberger, J., & Ort, D. R. (2006). Food for thought: Lower than expected crop yield stimulation with rising CO2 concentrations. *Science, 312*, 1918–1921.

Maize Information Guide - MIG (2014) http://www.arc.agric.za/arc-gci/Pages/MIG/MIG-2014.aspx Accessed 15 Dec 2018.

Martre, P., Wallach, D., et al. (2014). Multimodel ensembles of wheat growth: Many models are better than one. *Global change biology, 21*. https://doi.org/10.1111/gcb.12768.

Meadows, M. E. (2006). Global change and southern Africa. *Geographical Research, 44*, 135–145.

Nel, A. A., & Bloem, A. A. (2006). The delta yield procedure for nitrogen fertilisation of maize in South Africa. *South African Journal of Plant and Soil, 23*, 203–208.

National Planning Commission – NPC (2012) National Development Plan Vision 2030: Our future make it work. Available at: http://www.dac.gov.za Accessed on 10 Feb 2019.

Ncube, B., Dimes, J. P., van Wijk, M. T., Twomlow, S. J., & Giller, K. E. (2009). Productivity and residual benefits of grain legumes to sorghum under semi-arid conditions in southwestern Zimbabwe: Unravelling the effects of water and nitrogen using a simulation model. *Field Crops Research, 110*, 173–184.

Ncube, B., Twomlow, S. J., van Wijk, M. T., Dimes, J. P., & Giller, K. E. (2007). Productivity and residual benefits of grain legumes to sorghum under semi-arid conditions in southwestern Zimbabwe. *Plant and Soil, 299*, 1–15.

Rosenzweig, C., Hillel, D. (2015) Handbook of Climate Change and Agroecosystems: The Agricultural Model Intercomparison and Improvement Project (AgMIP) Integrated Crop and Economic Assessments — Joint Publication with American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America. https://doi.org/10.1142/p970.

Ruane, A.C., Winter, J.M., McDermid, S.P., Hudson, N.I. (2015a) AgMIP climate datasets and scenarios for integrated assessment. In handbook of climate change and Agroecosystems: The agricultural model Intercomparison and improvement project (AgMIP) integrated crop and economic assessments, part 1. C. Rosenzweig and D. Hillel, Eds., ICP series on climate change impacts, adaptation, and mitigation Vol. 3. Imperial college press, pp. 45-78, doi: 10.1142/9781783265640_0003.

Ruane, A. C., Goldberg, R., & Chryssanthacopoulos, J. (2015b). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation. *Agricultural and Forest Meteorology, 200*, 233–248.

Ruane, A. C., & McDermid, S. P. (2017). Selection of a representative subset of global climate models that captures the profile of regional changes for integrated climate impacts assessment. *Earth Perspective, 4*, 1–20. https://doi.org/10.1186/s40322-017-0036-4.

Saseendran, S.A., Ahuja, L.R., Ma, L., Timlin, D., Stockle, C.O., Boote, K.J., Hogenboom, G. (2008) Current water deficit stress simulations in selected agricultural system models. In: Ahuja LR, Reddy VR, Saseendran SA, Yu Q (Eds) Response of crops to limited water: Understanding and modeling water stress effects on plant growth processes. ASA , CSSA, SSSA, Madison, WI, USA.

Schulze, R.E. (2007). *Climate change and the agricultural sector in South Africa: An assessment of findings in the new millennium, ACRU report 55, School of bio-resources and Environmental Hydrology Engineering*. Pietermaritzburg: University of KwaZulu-Natal.

Schulze, R.E., Hallowes, L.A., Horan, M.J.C., Lumsden, T.G., Pike, A., Thornton-Dibb, S., Warburton, M.L. (2007) South African quaternary catchments database. In: Schulze RE (ed) south African atlas of climatology and Agrohydrology. WaterResearch commission, Pretoria, RSA, WRC report 1489/1/06, section 2.3.

Smithers, J., Schulze, R.E. (1995) ACRU agrohydrological modelling system user manual. WRC report. TT 70/95, Water Research Commission, Pretoria.

Southern Africa Development Community – SADC (2013) Agricultural & Food Security. Available at: www.sadc.int/themes/agriculture-food-security. Accessed 20 December 2018.

Statistics S.A. (2005). *Census of commercial agriculture, 2002*. Pretoria: Financial and Production Statistics.

Statistics S.A. (2010). *Census of commercial agriculture 2007*. Pretoria: Financial and Production Statistics.

Statistics S.A. (2012a). *Agricultural Survey 2011*. Pretoria: Financial and Production Statistics.

Statistics, S.A. (2012b) Poverty profile of South Africa: Application of poverty lines on the LCS 2008/2009.Available at: http://www.statssa.gov.za/publications/Report-03-10-03/Report-03-10-032009.pdf Accessed 10 March 2019.

Statistics S.A. (2017). *Census of commercial agriculture 2017*. Pretoria: Statistics South Africa.

Tadross, M.A., Jack, C., & Hewitson, B. C. (2005). On RCM-based projections of change in southern African summer climate. *Geophysical Research Letters, 32*(23), L23713.

Valdivia, R., Antle, J. M., & Stoorvogel, J. J. (2012). Coupling the tradeoff analysis model with a market equilibrium model to analyze economic and environmental outcomes of agricultural production systems. *Agricultural Systems, 111*, 85–95.

Valdivia, R., Antle, J.M., Rosenzweig, C., Ruane, A.C., Vervoort, J., et al (2015) Representative Agricultural Pathways and Scenarios for Regional Integrated Assessment of Climate Change Impacts, Vulnerability, and Adaptation. In Handbook of Climate Change and Agroecosystems: The Agricultural Model Intercomparison and Improvement Project (AgMIP) Integrated Crop and Economic Assessments, Part 1. C. Rosenzweig and D. Hillel, Eds., ICP Series on Climate Change Impacts, Adaptation, and Mitigation Vol. 3. Imperial College Press, pp. 45–78, doi:10.1142/9781783265640_0003.

Van Biljon, J. J., Fouche, D. S., & Botha, A. D. P. (2008). The lower and upper threshold values, biological optimum and mineralization of nitrogen in the main maize producing soils of South Africa. *South African Journal of Plant and Soil, 25*, 8–13.

Zampieri, M., Ceglar, A., Dentener, F., et al. (2019). When will current climate extremes affecting maize production become the norm? *Earth's Future, 7*, 113–122. https://doi.org/10.1029/2018EF000995.

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