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Abstract
Climate change impact assessments on agriculture in southern Africa are mostly carried out at large spatial scales, risking missing out on local impacts and adaptation potential that reflect the range of multiple and unique bio-physical and agronomic conditions under which farmers in the region operate. This study investigated how climate change may affect yields of various major food crops in specific locations in the region; maize and sorghum (Mohale's Hoek – Lesotho and Big Bend – Swaziland), maize and groundnut (Lilongwe – Malawi). Using statistically downscaled climate projections from nine GCMs and the DSSAT crop model and simulating selected agronomic strategies practised in each location, the study confirmed that impacts of climate change on crop yields in southern Africa vary across locations and crops. Despite various uncertainties associated with such assessments, the results showed that crop yields were predominantly projected to decline in Big Bend (maize (-20%); sorghum (-16%)) and Lilongwe (maize (-5%); groundnut (-33%)). However, crop yields in Mohale's Hoek, located in a high altitude region historically prone to cold related crop yield losses were on average projected to increase (maize (+8%) and sorghum (+51%)). The geographical variation of yield projections highlights the importance of location specific climate change impact assessments. The exploration of local agronomic management alternatives revealed prospects for identifying locally relevant adaptation strategies, which cannot easily be captured at larger scales.

Key words: agronomic practices, cereals, climate change, groundnut, modeling

1. Introduction

Agriculture is one of the most climate dependent of human activities (Hansen 2002), particularly in Sub-Saharan Africa (SSA) where close to 70% of the population depends on small scale agriculture (Cooper et al. 2008). This makes SSA extremely prone to the effects of climate change and variability. The Intergovernmental Panel on Climate Change (IPCC), 2007 states that by 2050, crop yield losses could reach up to 50% in some countries in SSA. Compounded by increased population and low adaptive capacity, the crop yield losses will severely compromise food security in Africa. In a review study of projected climate change impacts in the 21st century, Zinyengere et al. (2013) show that while there is significant uncertainty about the impact of climate change in the early 21st century (2020s), projected impacts further into the 21st century are robust, showing that climate change will negatively impact crops in southern Africa. Recent studies in Africa concur and suggest similar negative impacts on crops (Knox et al., 2012; Berg et al., 2013; Liu et al., 2013; Waha et al., 2013; Muller, 2013). Clearly, food security and livelihoods on the continent are at risk.

The majority of studies on climate change impacts on agriculture in SSA are commonly performed at large spatial scales, aggregated over entire countries, the region or the continent as a whole (Zinyengere et al. 2013). This kind of assessment leads to generalised and broad conclusions about the impact of climate change on crop production, which are not reflective of impacts at farm or community level. While these types of studies might be useful for national and regional planning, they run the risk of missing out on local peculiarities, where impacts vary considerably in both space and time. At coarse scales, it is difficult to sensibly identify useful on-farm adaptive measures. Large scale studies usually make broad-brush recommendation of adaptation strategies over large areas, which may not speak to local small holder dry land farmers. These farmers operate under peculiar conditions and practices more often emanating from personal/community experience, culture, financial and physical resources, and varying over short spatial scales. In order to understand how climate change may affect crop production in the systems and conditions that small holder dry land farmers operate and to identify adaptation strategies suited to those conditions, climate change impact studies need to be performed at high spatial resolutions (Thornton et al., 2011, Lobell et al., 2008). The few studies that have carried out such assessments in southern Africa were limited in the number of crops studied e.g. maize alone (Walker and Schulze, 2008 and Abraha and Savage, 2006) and focused on one location thereby lacking a simultaneous analysis of impacts in the region. Furthermore, studies do not attempt to explicitly assess the impacts of climate change with agronomic scenarios representative of local farming practices.

This study presents a location specific climate change impact assessment for dry land crop production in southern Africa. Three districts located in southern Africa (Mohale’s Hoek - Lesotho, Big Bend - Swaziland and Lilongwe - Malawi) with unique agro-ecological conditions and cropping practices were selected for the study. Climate projections were downscaled from nine Global Circulation Models (GCMs) for the three locations and used to drive a crop model to simulate impacts on three major southern African crops (maize, sorghum and groundnut). Projected baseline (1961-2000) and future (2046-2065) climate scenarios for two contrasting Special Report on Emission Scenarios (SRES) representing low (B1) and high (A2) future carbon dioxide (CO_2) emissions were used (Nakicenovic et al., 2000). Scenarios representing some agronomic strategies practiced by dry land farmers in each location were also simulated to provide insight into their potential for adaptation.

2. Methodology

2.1 Study location

Study locations were selected to represent a diversity of agro-ecological and agronomic conditions in southern Africa while crops were selected depending on local and regional importance to food security as follows; maize and sorghum in Big Bend; maize and sorghum in Mohale's Hoek; maize and groundnut in Lilongwe. Big Bend (-26.82°, 31.93°) is found in the low veld of Swaziland, a region considered marginal for maize and more suited to small grains. Temperatures are high with a monthly average of 30 °C during the cropping season (Manyatsi et al., 2013). Mohale's Hoek (-30.15°, 27.47°) is located in the low veld, the main agricultural region of Lesotho, a high altitude country prone to cold related crop yield losses. Average annual minimum temperatures are below 10 ° C (Gwimbi et al., 2013). Lilongwe (-13.98°, 33.78°) is located in a mid-altitude region that is considered one of the most productive for cereals in Malawi (Saka et al., 2013). Temperatures are moderate. All three locations experience uni-modal summer rainfall between October and April, averaging 507 mm, 602 mm and 810 mm during the cropping season for Big Bend, Mohale's Hoek and Lilongwe respectively. Agriculture in all locations is dominated by dry land small holder production on old sandy clay loam soils.

2.2 Scenario based impact assessment

In this study, the Decision Support System for Agro- technology Transfer (DSSAT) deals with the crop growth (Jones et al., 2003). To assess the impacts of climate change on crops at a fine level scale (farm/community), local climate variables (e.g. maximum temperature, minimum temperature, solar radiation and precipitation), crop and soil parameters, and management practices were crucial inputs.

2.2.1 Climate data and scenarios

The study used nine Comprehensive Model Intercomparison Project 3 (CMIP3) GCMs data (Meehl et al., 2007) as summarized in Table 1. The data was downscaled to a climate station in each study district to represent climate projections in each location for a baseline (1961 - 2000) and future period (2046 - 2065). The statistical downscaling was done using the self-organising maps (SOMs) approach by Hewitson and Crane (2006). Daily weather records (minimum and maximum temperatures and rainfall) were obtained from national meteorological institutions in each study country. Solar radiation was estimated with a routine based on daily minimum and maximum temperatures, latitude and elevation using the methods of Allen et al. (1998) and Ball et al. (2004) which were shown to be efficient over southern Africa (Hachigonta, 2011). For each of the nine GCMs, contrasting scenarios, namely the Intergovernmental Panel on Climate Change Special Report on Emission Scenarios (IPCC SRES) carbon dioxide (CO_2) emissions were used, respectively designated for B1 (low emission) and A2 (high emission).

2.2.2 Crops, soils and management practices

DSSAT was driven by the above climate scenarios. The crops, soils and management scenarios used were summarised in Table 2. Soil texture was sandy clay loam for all locations although with different characteristics representative of each study district as shown by the varying soil bulk density (BD), organic carbon content (OC), clay content percentage (CL) and silt content percentage (SI) of the top soils. Crop cultivars used were selected from those previously used in the past, with enough experimental data for crop model calibration. Similar cultivars in the DSSAT database were tailored to suit those shown in Table 2. Management practices included planting density, fertilizer amount and planting date. A planting density representative of those practiced by small holder dry land farmers in each location was used. Two fertilizer applications were used in combination with two planting dates to make four agronomic management scenarios. Agronomic management scenarios included “common” (an estimate of what local farmers commonly use) and “expert recommended” (what local expects recommend for farmers) agronomic practices. These were obtained from agricultural reports in respective countries. Explored fertilizer amounts shown in Table 2 translate common fertilizer (CF) amounts and those recommended by experts (RF). Two planting dates were considered, an early planting date (EP) corresponding to dates small holder dry land farmers usually sow in response to the first rains, and a later planting date (LP) as recommended by experts. Combinations of two treatments of two fertilizer amounts and two planting dates were simulated in combinations as follows: EP with RF; EP with CF; LP with RF; LP with CF.

DSSAT was calibrated and validated for simulating crop yields under local conditions in study locations (Zinyengere et al., 2014). The locally calibrated and validated DSSAT model was used to simulate crop yields for the baseline (1961- 2000) and future (2046-2065) periods by changing climate parameters and holding constant all other factors (soils, cultivars, management strategies, CO_2 concentration). The effect of CO_2 was not investigated because it is still poorly understood and C4 crops, the major crops studied here (except groundnut) are known to have a very small response to the increase of atmospheric CO_2 (Long et al., 2006; Tubiello et al., 2007; Ainsworth and Ort, 2010; Gornall et al., 2010).

2.3 Confidence and uncertainty assessment

In this study, uncertainty in the projected impact of climate change on crops was assessed through methods similar to Ruiz-Ramos and Minguez (2010) as follows:

1) *Sign of mean yield change* (negative or positive): This was done for each crop and location under study for each combination of SRES CO_2 emission, GCM and management scenarios. Coincidence of GCMs and management scenarios with the same sign of change across CO_2 emission scenarios was used to ascertain the degree of confidence in the direction of yield change.

2) *Comparisons of time series means*: Combinations of time series were compared for coincidence in projected yields through testing for significant differences in means. A two tailed t-test with unequal variance was used. For each location, emission scenario and management strategy, each time series was compared two by two with the other eight to represent the influence of GCMs on the overall coincidence of time series. For location, emission scenario and GCM, each time series was also compared two by two with the other seven to represent the influence of management strategies on overall coincidence of time series. The degree of coincidence was measured as the percentage of pairs showing a non-significant difference, at the 0.05 level of significance. A large degree of coincidence is associated with low uncertainty and *vice versa*. This also provided insight into the strength of the source of uncertainty (GCMs, management strategy etc.).

3) *Comparisons of yield variability*: Mean coefficients of variation were compared for CO_2 emission scenarios, GCMs and management scenarios, thereby identifying the sources of large uncertainty through high interannual variability.

3. Results

3.1 Climate change projections

Climate models consistently projected increased temperatures for all study locations. Projected temperature changes showed a mean increase of 1.7 - 2.4 °C, with a range of 1.3 – 2.7 °C (Table 3). Mohale's Hoek showed the highest projected increase in temperature, recorded under the A2 scenario while Big Bend had the least temperature increase. In contrast, the projected change in rainfall varied from one location to the other and in some cases depending on the CO_2 emission scenario. Projected mean rainfall changes were small, within a 7% average, although varying considerably across GCMs. Projected mean rainfall changes for Big Bend were a decline of -2.9% for the B1 scenario and an increase of +4.2% for the A2 scenario with a range of projections of -12% to +5% and -7% to +10% respectively (Table 3). Projected mean rainfall for Mohale's Hoek increased by +5.5% (B1) and +7% (A2) with a range of -1% to +16% and -1% to +18%. Mean rainfall in Lilongwe decreased only slightly with a range of -15% to +7% (B1) and -9% to +7% (A2) (Table 3).

Climate projections exhibited the seasonality of temperature in all locations (Fig 1). Similarly, seasonality of rainfall was shown in the projections, with wet summers (October – April) and dry winters (May – August). Mean monthly rainfall for Mohale's Hoek increased slightly during the summer cropping season (October – April), peaking towards the end of the season. Projected rainfall for Big Bend was higher than the baseline during the early months of the cropping season (October and November). Rainfall remained the same (A2) or declined during the perennial peak period of December, January and February (B1). Projected rainfall for Lilongwe peaked during the perennial peak period. Mean changes were negligible. While projected rainfall changes were variable and uncertain, the projected monthly temperature changes, showed strong signals and consistency, towards an increase (Fig 1).

3.2 Projected impacts on crop yields

Projected mean crop yield changes for Big Bend (Table 4) showed a consistent decline for maize and sorghum yields. Average yield decline across all scenarios was 20% and 16% for maize and sorghum respectively, with a range from -43.8 to -6% and -40% to +8.7%. Yield increase was projected for sorghum under the agronomic practice of late planting with common fertilizer (LP with CF). Sorghum yields under a scenario of early planting with common fertilizer (EP with CF) were the most severe, consistently above a decline of 25% across all climate scenarios.

Projected mean maize yield changes for Mohale's Hoek were large and the most inconsistent across climate scenarios (-60.4% to +120%), albeit with a mean increase of 8% across all scenarios (Table 5). However, under scenarios were the management strategy of late planting (LP) was simulated, shown as LP with RF and LP with CF in Table 5, mean maize yields largely increased. Projected increase in mean maize yields averaged 18% and 15% for the two management scenarios respectively. The GISS climate model largely contributed to the variation in projected mean maize yield changes (-27% to +120%). Sorghum yields for Mohale's Hoek were projected to increase from baseline, mostly above 25%, with an average increase of 51% across all scenarios. Under some scenarios, sorghum yields were projected to increase by up to three times the baseline yields.

Projected impacts for Lilongwe were of a slight decline in mean maize yields and more pronounced decline in groundnut yields. Projections were consistent across all scenarios with an average decline of 5% for maize and 33% for groundnut, with a range of -11.3% to +2.9% and -51% to -20% respectively. Only one simulation treatment was made for the management practice of fertilizer application for groundnut. Simulations of 0 kg N/ha were made, following common and recommended practice in Lilongwe, hence only two scenarios were shown for groundnut.

3.3 Uncertainty and confidence degrees

High agreement on the sign of yield change was found across all locations and crops except for maize in Mohale's Hoek (Table 4, 5 and 6). High coincidence was also found across management strategies (45 – 88%) despite the large disparity of climate projections from

GCMs (Table 7). The mean degree of coincidence was highest in maize yield projections for all locations. Lowest coincidence of time series was found for EP with RF and LP with RF for sorghum in Big Bend and groundnut in Lilongwe, where less than half the time series had non-significant differences. Treatments of EP with CF for maize and sorghum in Big Bend showed 100% coincidence among time series. Average coincidence was low among GCMs scenarios, ranging from 19 to 52%. Lilongwe had the lowest agreement across time series for both maize and groundnut, averaging 25 and 19% respectively (Table 7).

Yield response variation across all management strategies ranged from a mean CV of 7% to 53% (Fig 2). CVs for each management treatment were highest for sorghum in Mohale's Hoek, between 30 and 53%. Simulated CVs were also high for Big Bend, reaching up to 40% for maize and sorghum. Among the high CVs in Big Bend, were notably low CVs for sorghum (12 %) under EP with CF (Fig 2a). Similarly, yield variation was low for maize in Mohale's Hoek, particularly for the LP with RF and LP with CF treatments (Fig. 2b). Overall yield variation was lowest in Lilongwe (7 – 28%), with groundnuts having higher CVs than maize. Clustering CVs by GCMs as shown in Fig. 4 revealed high variation in sorghum yields for Mohale's Hoek, peaking at a CV of 70%. Big Bend had the second highest CVs for both maize and sorghum of between 13 and 42%. Least variation was found for maize in Lilongwe (7 - 15%).

4. Discussion

4.1 Crop yield changes

The apparent effect of climate change on crops in this study was a decline in crop yields due to higher temperatures which potentially reduced the crop growth season and thereby reduced the yield in the arid area at Big Bend. This effect was however compensated in the high altitude and cooler location (Mohale's Hoek), leading to increased mean yields. Maize and sorghum yields in Big Bend were shown to be negatively affected by temperature increase due to climate change. Being a dry area, increase in temperature along with little or no increase in future mean total rainfall, Big Bend becomes even less conducive for rainfed maize and sorghum. Maize and groundnut yield changes in Lilongwe were also projected to be negative. However, maize yield changes were small compared to the other locations. This is due to the moderate Lilongwe climate and the smaller changes projected for rainfall and temperature. Despite the moderate changes in climate, groundnut yields were severely affected, with an average decline in yield of 33%. A lack of fertilizer application (P and K) as is common with small holder communities in Lilongwe may lead to larger negative impacts for groundnut. Simulated impacts for Mohale's Hoek showed a mix of positive and negative impacts for maize and positive impacts for sorghum. Positive impacts were more consistent across GCMs scenarios for some management scenarios. Lesotho being a high altitude country that perennially experiences cold related crop yield losses benefits from favourable crop growth conditions created by warming temperatures. Mean minimum temperatures during crucial growth periods (grain filling) were projected to rise above 10 °C (base temperature for some maize varieties) thereby reducing crop yield losses due to dormancy, slowed grain filling and cold stress. Coupled with the peaking of rainfall during the same period (February, March and April), conducive conditions for crop growth and increased yields were created. Sorghum being more tolerant to heat and water stress benefited even more from a warmer and wetter climate in Mohale's Hoek (Table 5). However, large responses of up to three times the baseline yields could be related to an over-sensitive sorghum model response to climate.

Broadly negative impacts projected for crops in Big Bend and Lilongwe are largely consistent with studies in the region, which are predominantly large scale. Jones and Thornton (2003) and Thornton et al. (2011) projected that maize yields will likely decline in most countries in southern Africa by an average of 10% and 16% respectively by mid-21st century. Parry et al. (2004) projected a decline of 5 – 30% in cereals yields and Schlenkler and Lobell (2010) projected a decline of up to 22%, 17% and 18% for maize, sorghum and groundnuts respectively. In a study involving eight countries in southern Africa, Hachigonta et al. (2013) also broadly projected a decline in crop yields. Similarly, in a local study in South Africa, Walker and Schulze (2008) projected an average decline of maize yields of 30%. Projections of increased crop yields as a result of climate change in Lesotho have largely been unexplored. Recent studies by Malebajoa (2010) and Gwimbi et al. (2013) suggest a decline in maize yields in Mohale's Hoek by 2050 of more than 25% and a decline in sorghum yields of up to 10% and 25% respectively. However, Gwimbi et al. (2013) give indications of possible sorghum yield increase in other parts of Lesotho. In this study, yield gains for maize and sorghum were robustly apparent. While results from this study globally agree with large scale studies in the region, it draws out the location and crop specificity of impacts not necessarily accounted for by large scale studies. In Mohale's Hoek, the study showed that impacts are likely to evolve differently from those presented by common national and regional projections. It was therefore apparent that broad-brushed recommendations for suitable strategies to adapting crop production to climate change in dry land systems were not sufficient. Finer scale investigations will be required.

4.2 Agronomic management strategies

Defining adaptation strategies for an uncertain future is a challenge. However, this study showed that valuable information regarding the potential of locally practised agronomic strategies for adaptation to climate change can be obtained through high resolution simulations. The study showed that for most locations and crops, despite the incoherent climate projections from GCMs (rainfall), there was a considerable coincidence and agreement in simulated yield impacts per agronomic practise (Table 7). Furthermore, agronomic strategies that have a strong influence on the overall projected impacts can be identified, e.g. the practice of early planting with common fertilizer application (EP with CF) in Big Bend, which had very low yield variation (Fig. 2a) and the practice of late planting with recommended fertilizer (LP with RF) or common fertilizer (LP with RF) for maize in Mohale's Hoek (Fig. 2b). These practices corresponded to strong negative impacts for maize and sorghum in Big Bend (Table 4) and strong positive impacts on maize yields in Mohale's Hoek (Table 5). This suggested that in some locations, agronomic strategies practiced by farmers may exacerbate the negative impacts of climate change (Big Bend). In this case, the common practise of supplying low fertilizer rates and planting earlier exposes crops to unfavourable growth conditions. In other locations, agronomic practices provided yield benefits. Late planting of maize in Mohale's Hoek provided the opportunity to take advantage of the peaking of rainfall towards the end of the rainfall season (February, March, April), regardless of the fertilizer amounts applied.

Insight about the potential contribution of agronomic strategies of local farmers to climate change adaptation is difficult to obtain with coarse scale studies as indicated by Lobell et al. (2008) and Thornton et al. (2011). Finer scale studies can provide more detailed information. In Lesotho, planting late is not a common practise or considered a beneficial alternative, yet through fine scale simulations, this study showed that late planting could provide yield benefits as the climate changes. This kind of information provides better understanding of areas for further assessments and stakeholder engagement towards identifying agronomic strategies better suited to changing climates in particular farming communities and possibly fostering adoption.

4.3 Uncertainties and limitations

Overall, while uncertainty remains a factor in this study, a clear trend was established, decreasing crop yields in Big Bend and Lilongwe and increasing crop yields in Mohale's Hoek. GCM scenarios tended to be the primary influence on total uncertainty in studies that used a single crop model (Challinor et al., 2009). This was apparent in our study, where yield variation was very driven by GCM scenarios was high (Fig. 3b). However, our study also demonstrated that agronomic management scenarios can contribute significantly to overall uncertainty. In Mohale's Hoek (sorghum) and Big Bend (maize and sorghum), changing the agronomic strategies influenced uncertainty considerably as shown by high CVs of up to 40% (Fig. 2a and 2b). For Big Bend, this was almost as high as variations introduced by GCM scenarios. Emission scenarios on the other hand weren't as important for most locations and crops as shown by the limited differences in simulated variations (Fig. 2 and 3). Exploring uncertainties from management scenarios in addition to GCMs is vital in impact assessment.

A number of limitations remain and could form areas for further research. This study did not investigate the direct effect of increased CO_2 on crops. Modelling the effect of increased CO_2 on various crops is still a matter of debate (Long et al., 2006; Ewert et al., 2007; Tubiello et al., 2007; Ainsworth and Ort, 2010) and predictions of crop production under elevated CO_2 and climate change conditions require more research (Tubiello and Ewert (2002); Tubiello et al., 2007). However, some studies have suggested that elevated CO_2 may reduce the negative impacts of climate change on crops especially C3 crops (Tingem et al., 2008), others state that C4 plants (e.g. maize and sorghum studied) do not respond much to higher ambient CO_2 (Sultan et al., 2013). While not addressed in this study, the modelling of crop responses to elevated CO_2 is a major source of uncertainty in climate change impact studies (McGrath and Lobell, 2013), more insight could be provided through further studies.

Although crop modelling contribution to uncertainty was sampled by simulating various agronomic practices, our study used a single crop model thereby limiting the quantification of uncertainty. Future studies may consider the use of multiple crop models. Such a process is currently underway with the Agricultural Model Intercomparison Project (AgMIP) and can improve the quantification of uncertainty in impact studies (Rosenzweig et al., 2013). While an assessment with multiple crop models was difficult to carry out in our study given data and time limitation, future studies that use single crop models and simulate crop response to agronomic management strategies could perform a sensitivity analysis to get a clearer understanding of how the model responds to the different agronomic practices, over and above the calibration of the crop model.

5. Conclusion

Through a location specific assessment, this study was able to demonstrate that impacts of climate change on crops in southern Africa will be significant, but vary across locations and crops. Some places will be impacted negatively while other places will benefit depending on crop species. Benefits are likely in Mohale's Hoek, a high altitude area where temperatures are cooler than most of the region. Through simulating location specific agronomic practices of farmers, the study showed that on farm practices could exacerbate the impacts of climate change or help to take advantage of potential benefits. There exists a high confidence in the direction of crop yield changes due to climate change (positive or negative), except for maize at Mohale's Hoek and that existing uncertainties emanate mostly from climate projections and agronomic management scenarios.

The demonstrated location and crop specificity of the impacts of climate change in the region demand site-specific design of adaptive measures with perspectives that focus on the vulnerable dry land farmers, especially small holders who are considered the most vulnerable. Separating projections of impacts of climate change by location and crop and simulating locally relevant agronomic practises helps avoid the recommendation of one-size-fits-all adaptation strategies brought about by broad-brush conclusions made over large areas. As such, it is important to investigate the potential of various locally practised agronomic management strategies for the efficient adaptation of dryland farming to climate change. This can be done with explicit consideration of the bio-physical and socio-economic conditions that local dry land farmers in the region operate. Location specific study along with a bottom-up approach can provide finer information to feed into outcomes of larger scale studies and provide an avenue for developing relevant policies that support autonomous responses by local farmers to climate change.

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Table Error! No sequence specified. Comprehensive Model Intercomparison Project 3 (CMIP3) Global Circulation Models (GCMs) from which climate scenarios were obtained.

Name used	Originating group(s)	Country	Model full name	Primary reference
CCMA	Canadian Centre for Climate Modeling & Analysis	Canada	CGCM3.1 (T47)	Flato and Boer, 2001
CNRM	Météo-France / Centre National de Recherches Météorologiques	France	CNRM-CM3	Salas-Mélia et al., 2005
CSIRO	Australia's Commonweath Scientific and Industrial Research Organisation	Australia	CSIRO_MK3.5	Gordon et al. 2002
GFDL	US Dept. of Commerce / NOAA / Geophysical Fluid Dynamics Laboratory	USA	GFDL-CM2.1	Delworth et al., 2006
GISS	NASA / Goddard Institute for Space Studies	USA	GISS-ER	Russell et al., 2000
IPSL	Institute Pierre Simon Laplace	France	IPSL-CM4	Dufresne et al., 2005
MIUB	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, Model and Data group at MPI-M	Germany / Korea	ECHO-G	Legutke and Voss, 1999
MPI	Max Planck Institute for Meteorology	Germany	ECHAM5/MPI-OM	Jungclaus et al., 2006
MRI	Meteorological Research Institute	Japan	MRI-CGCM2.3.2	Yukimoto et al., 2001

Table 2 Showing simulated conditions; agronomic management (planting density, fertiliser application amount and timing and planting dates), soils (Bulk density (BD), Organic Carbon (OC), Clay content (CL), Silt Content (SI)) and mean crop yields per location and crop.

Location	**Big Bend**	**Mohale's Hoek**	**Lilongwe**
Soil	Sandy clay loam	Sandy clay loam	Sandy clay loam

			BD	OC	CL	SI	BD	OC	CL	SI	BD	OC	CL	SI
			1.6	0.3	30	11	1.4	1.1	21	37	1.5	0.8	28	9
Crop 1	**Name**		Maize hybrid: PAN473				Maize hybrid: PAN 473				Maize hybrid: MH 17			
	Mean yield (kg/ha)		1 700				2 200				2 700			
Management	**Plant density (plants/ha)**		30 000				33 000				37 000			
	Fertiliser application (kg N/ha)		Common		Recom-mended		Common		Recom-mended		Common		Recom-mended	
		Basal	7		16		10		25		35		23	
		Top	2		8		5		13		0		46	
	Planting dates	**Early**	Early - mid November				Mid November				Late November			
		Late	Early - mid December				Mid December				Late December			
Crop 2	**Name**		Sorghum: DC 75				Sorghum: PAN 845				Groundnut: Malimba			
	Mean yield (kg/ha)		1 800				850				700			
Management	**Plant density (plants/ha)**		60 000				60 000				45 000			
	Fertiliser application (kg N/ha)		Common		Recom-mended		Common		Recom-mended		Common		Recom-mended	
		Basal	4		20		8		25		0		0	
		Top	8		35		4		13		0		0	
	Planting dates	**Early**	Mid - late November				Mid November				Mid November			
		Top	Mid - late December				Mid December				Mid December			

Fertiliser was applied at planting (Basal) and at 4-5 weeks (Top). Two applications of fertiliser were simulated per crop and location i.e. common (as usually applied by farmers) and recommended (as suggested by experts). Planting dates included an early and late planting date per crop and location, simulated based on a date within a given period e.g. early – mid November being an early planting period for maize (PAN473) in Big Bend. Also shown are simulated mean yields and planting densities per crop and location.

Table 3 Mean change in projected climate between baseline (1961- 2000) and future (2046-2065) for two CO_2 emission scenarios; low (B1) and high (A2) and the range (min-max) of projections across all nine Global Circulation Models (GCMs).

		Temperature (°C)			**Rainfall (%)**
		Average	**Minimum**	**Maximum**	
Big Bend	B1	2.1 (1.6-2.5)	2.2 (1.6-2.6)	2.0 (1.6-2.4)	-2.9 (-12 to 5)
	A2	2.0 (1.6-2.2)	2.1 (1.7-2.4)	1.9 (1.5-2.1)	4.2 (-7 to 10)
Mohale's Hoek	B1	1.8 (1.3-2.3)	1.9 (1.3-2.4)	1.9 (1.3-2.3)	5.5 (-1 to 16)
	A2	2.4 (1.8-2.7)	2.4 (1.8-2.7)	2.4 (1.7-2.6)	7.0 (-1 to 18)
Lilongwe	B1	1.8 (1.4-2.2)	1.7 (1.3-2)	1.8 (1.4-2.3)	-2.4 (-15 to 7)
	A2	2.2 (1.8-2.6)	2.1 (1.7-2.6)	2.3 (1.9-2.7)	-1.1 (-9 to 7)

Table 4 Percentage mean maize and sorghum yield changes between baseline and future periods: Big Bend for nine Global Circulation Models (GCMs), four management treatments: early planting (EP), late planting (LP), common fertilizer (CF) and recommended fertilizer (RF), and two CO_2 emission scenarios: low (B1) and high (A2). GCMs references; see table 1. Light grey: yield change larger than twenty five percent.

	EP with RF		**LP with RF**		**EP with CF**		**LP with CF**	
	B1	**A2**	**B1**	**A2**	**B1**	**A2**	**B1**	**A2**
GCMs	***MAIZE***							
CCMA	-40	-34	-36.4	-28	-15.6	-18	-21.8	-14
CNRM	-17.7	-12	-10.5	-14	-20.6	-15	-12.5	-15
CSIRO	-32.6	-37	-14.3	-28	-30	-26	-13.4	-11
GFDL	-9.3	-4.7	-21.9	-15	-27.1	-22	-15.1	-7.4
GISS	-25.8	-20	-19.2	-16	-29.4	-18	-19	-16
IPSL	-19	-6	-21.3	-17	-11.5	-15	-9.6	-13
MIUB	-24.2	-25	-14.5	-16	-24.9	-25	-16.9	-13
MPI	-43.8	-24	-21.8	-24	-13.6	-23	-7.8	-15
MRI	-19.4	-12	-29.3	-22	-21.8	-20	-23.6	-19
SORGHUM								
CCMA	-39	-26	-40	-34	-28	-26	-13	-5
CNRM	-8	-10	-1.2	-10	-31	-30	8.7	6
CSIRO	-18	-28	-23.7	-27	-28	-28	-5.1	-14
GFDL	-9.9	0	-25	-16	-27	-26	-3.7	-1
GISS	-9	-9	-8.8	-6	-29	-30	2.5	1
IPSL	-19.1	-15	-9.6	0	-30	-32	6.2	6
MIUB	-12	-19	-23	-18	-31	-31	0	8
MPI	-26	-12	-18	3	-30	-26	-11	4
MRI	-21	-12	-28	-19	-30	-32	-10	-6

Table 5 Percentage mean maize and sorghum yield changes between baseline and future periods: Mohale's Hoek for nine Global Circulation Models (GCMs), four management treatments: early planting (EP), late planting (LP), common fertilizer (CF) and recommended fertilizer (RF), and two CO_2 emission scenarios: low (B1) and high (A2). GCMs references; see table 1. Dark grey: yield change larger than ten percent.

	EP with RF		**LP with RF**		**EP with CF**		**LP with CF**	
	B1	**A2**	**B1**	**A2**	**B1**	**A2**	**B1**	**A2**
GCMs	***MAIZE***							
CCMA	2.2	6.1	6.8	7.7	-18	-60.6	-13.4	-24.1
CNRM	10.4	11.2	25.9	23	-5.3	-1.5	14.7	27
CSIRO	2.8	0.6	10	5.9	-1	1.2	10.8	13.4
GFDL	1.3	-0.5	12.5	13.7	-11.9	2.5	-0.5	5.2
GISS	-5	8.2	61.8	68.2	-27	103	35.3	120
IPSL	7	11.6	10.5	16.2	1.6	-52	10.4	21.5
MIUB	4	1.6	30.6	29.2	-7.9	-8.9	11.5	17.1
MPI	-1.8	11	1.9	7.1	5.6	2.6	7	6.7
MRI	-6.1	-6.3	6	-5.7	4.4	8.6	13.3	-0.5
	SORGHUM							
CCMA	149.5	1.3	93.7	21.6	187.9	69.8	58.0	39.1
CNRM	33.1	33.6	29.8	32.2	55.0	68.0	48.5	48.8
CSIRO	18.8	215.9	17.6	79.7	7.0	101.2	64.7	156.3
GFDL	14.9	17.6	8.8	25.8	72.0	82.6	48.5	48.5
GISS	88.1		44.2		77.2		213.8	
IPSL	15.5	28.8	11.3	26.6	47.2	56.1	65.3	64.7
MIUB	37.9	41.3	31.9	32.1	49.7	55.0	84.6	84.6
MPI	-9.4	12.5	-1.7	20.6	37.1	48.5	54.3	51.6
MRI	8.3	1.3	6.7	6.1	51.5	48.5	37.8	37.9

Table 6 Percentage mean maize and sorghum yield changes between baseline and future periods: Lilongwe for nine Global Circulation Models (GCMs), four management treatments: early planting (EP), late planting (LP), common fertilizer (CF) and recommended fertilizer (RF), and two CO_2 emission scenarios: low (B1) and high (A2). GCMs references; see table 1. Light grey: yield change larger than twenty five percent.

	EP with RF		**LP with RF**		**EP with CF**		**LP with CF**	
	B1	**A2**	**B1**	**A2**	**B1**	**A2**	**B1**	**A2**
GCMs	***MAIZE***							
CCMA	-5.3	-0.5	-5.6	-5.5	0	-0.5	-5.8	-4
CNRM	-5.6	0	-5.8	-3.4	-4.5	-5.6	-5.9	-4.6
CSIRO	-1.6		-2.6		-4.2		-4.6	
GFDL	-6	0.6	-9.2	-7.2	-7	-5.6	-11.3	-10
GISS	-2.8	-3.2	-5.3	-5.2	-5.3	-0.2	-5	-9
IPSL	-3.5	-5.9	-7.8	-4.3	-3.8	-6	-6	-3.7
MIUB	-5.1	-5.4	-6.5	-1.1	-4.4	-5.8	-2.6	-1.2
MPI	-2.6	2.9	-8.4	-5.9	-6.2	-3.1	-5.8	-3.7
MRI	0.7	-6.7	-5.5	-9.3	1.1	-1.8	-2.5	-7.6
	GROUNDNUT							
CCMA					-32	-51	-22	-35
CNRM					-29	-47	-30	-41
CSIRO					-35		-25	
GFDL					-40	-47	-20	-21
GISS					-35	-37	-23	-26
IPSL					-31	-32	-22	-22
MIUB					-42	-44	-35	-32
MPI					-26	-35	-26	-26
MRI					-49	-45	-27	-27

Table 7 Degree of coincidence (percentage of time series showing non-significant differences). Represents percentage yield projection uncertainty per location and crops based on differences in time series by management strategy and GCM scenarios. Management and GCMs references: see tables 1 and 4.

	Big Bend		**Mohale's Hoek**		**Lilongwe**	
	Maize	**Sorghum**	**Sorghum**	**Sorghum**	**Maize**	**Groundnut**
Management						
EP with RF	70	42	66	71	81	42
LP with RF	56	45	89	67	97	49
EP with CF	100	100	86	77	91	-
LP with CF	91	68	68	72	83	-
Mean	**79**	**64**	**77**	**71**	**88**	**45**
GCMs						
CCMA	43	71	43	43	43	67
CNRM	29	43	29	29	0	0
CSIRO	43	57	29	43	0	0
GFDL	14	43	29	43	14	0
GISS	14	43	29	14	43	0
IPSL	43	57	43	43	14	0
MIUB	43	43	43	43	29	33
MPI	29	71	43	57	43	0
MRI	43	43	43	43	43	67
Mean	**33**	**52**	**37**	**40**	**25**	**19**

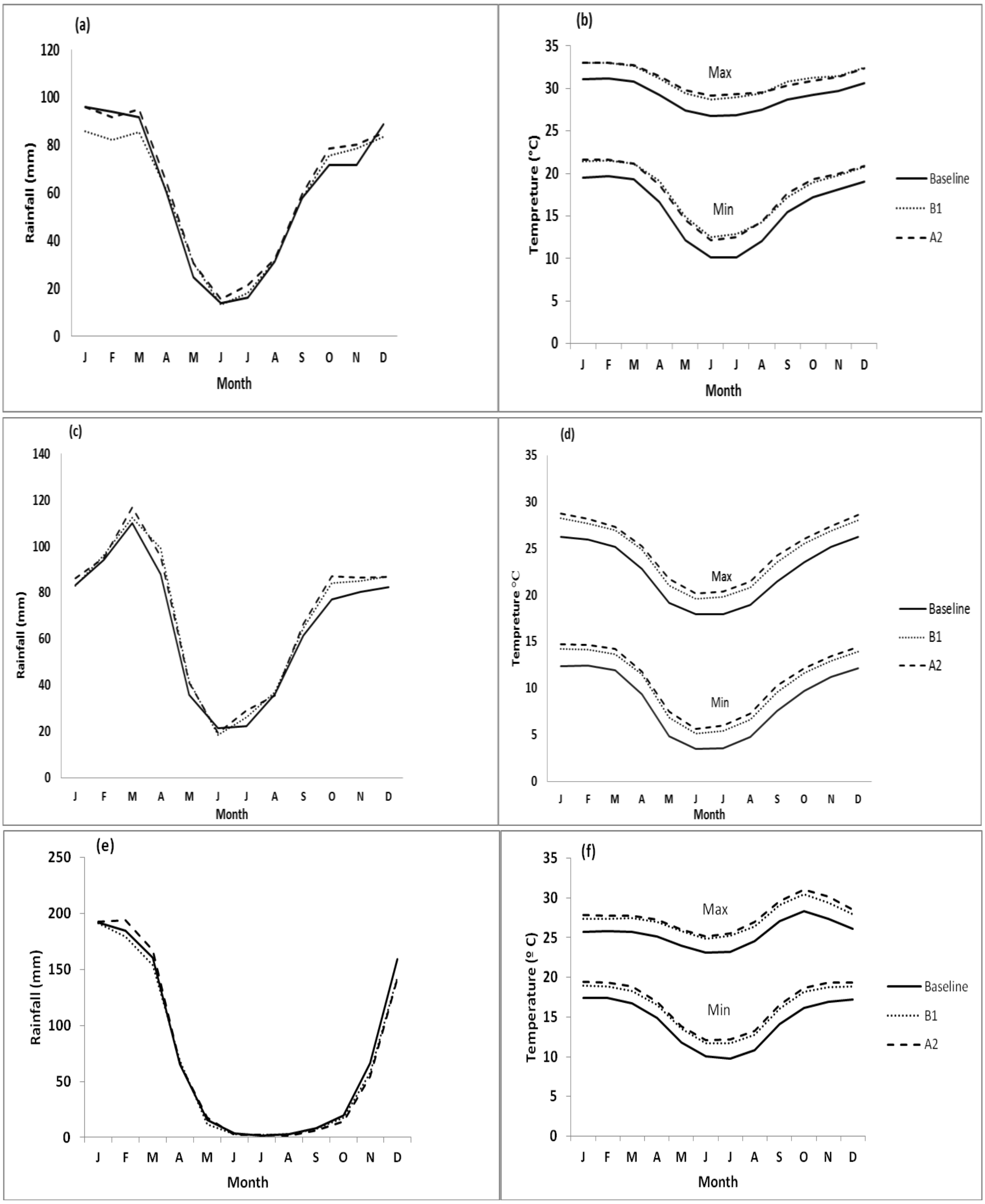

Fig 1 Projected ensemble mean monthly rainfall and temperature for Big Bend (a-b), Mohale's Hoek (c-d), and Lilongwe (e-f) for two emission scenarios: low (B1) and high (A2).

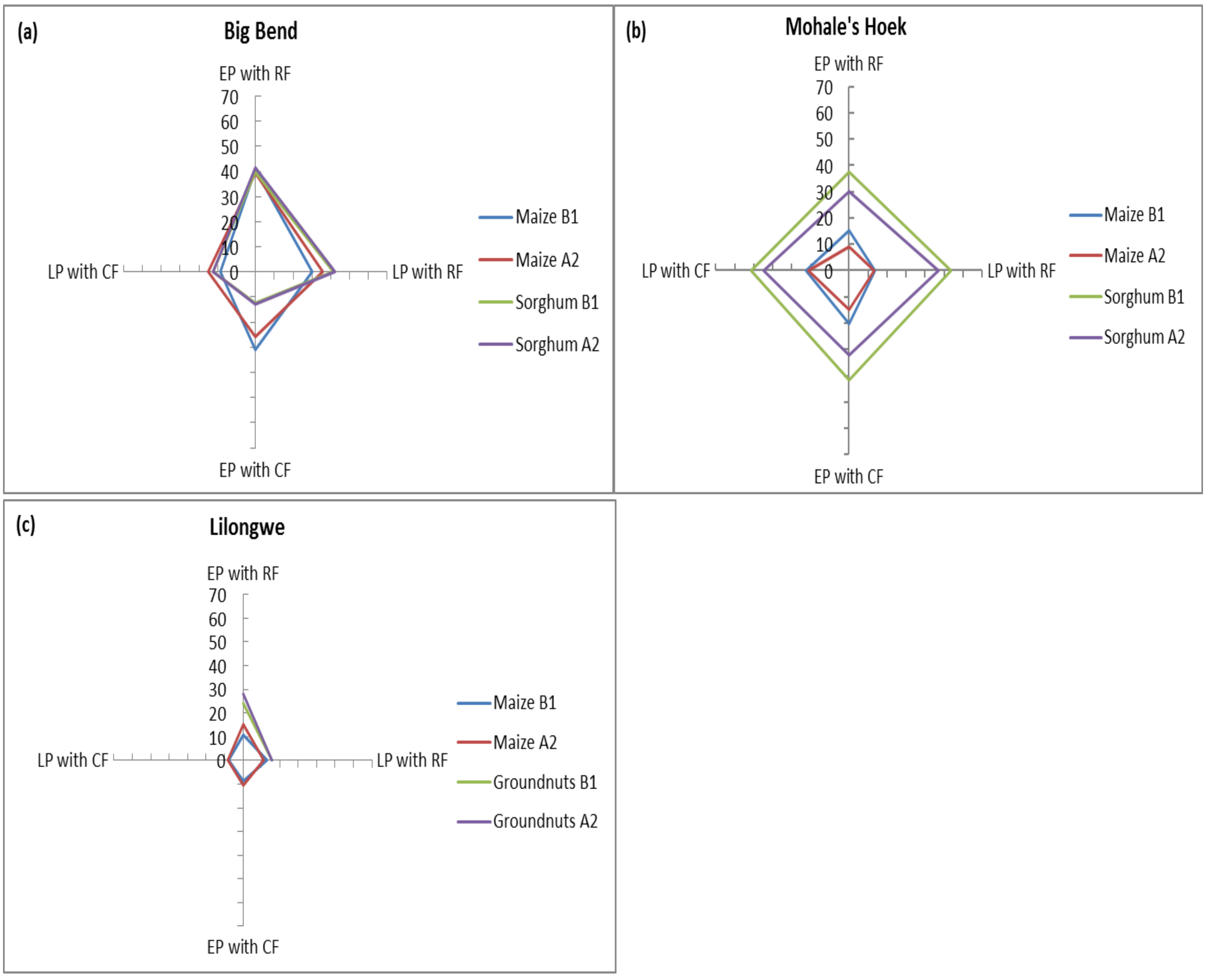

Fig 2 Mean percentage values of coefficient of variation. A measure of interannual variability of projected crop yields per locations and CO_2 emission scenarios B1 (low) and A2 (high), clustered by management strategy. Management references: see table 4.

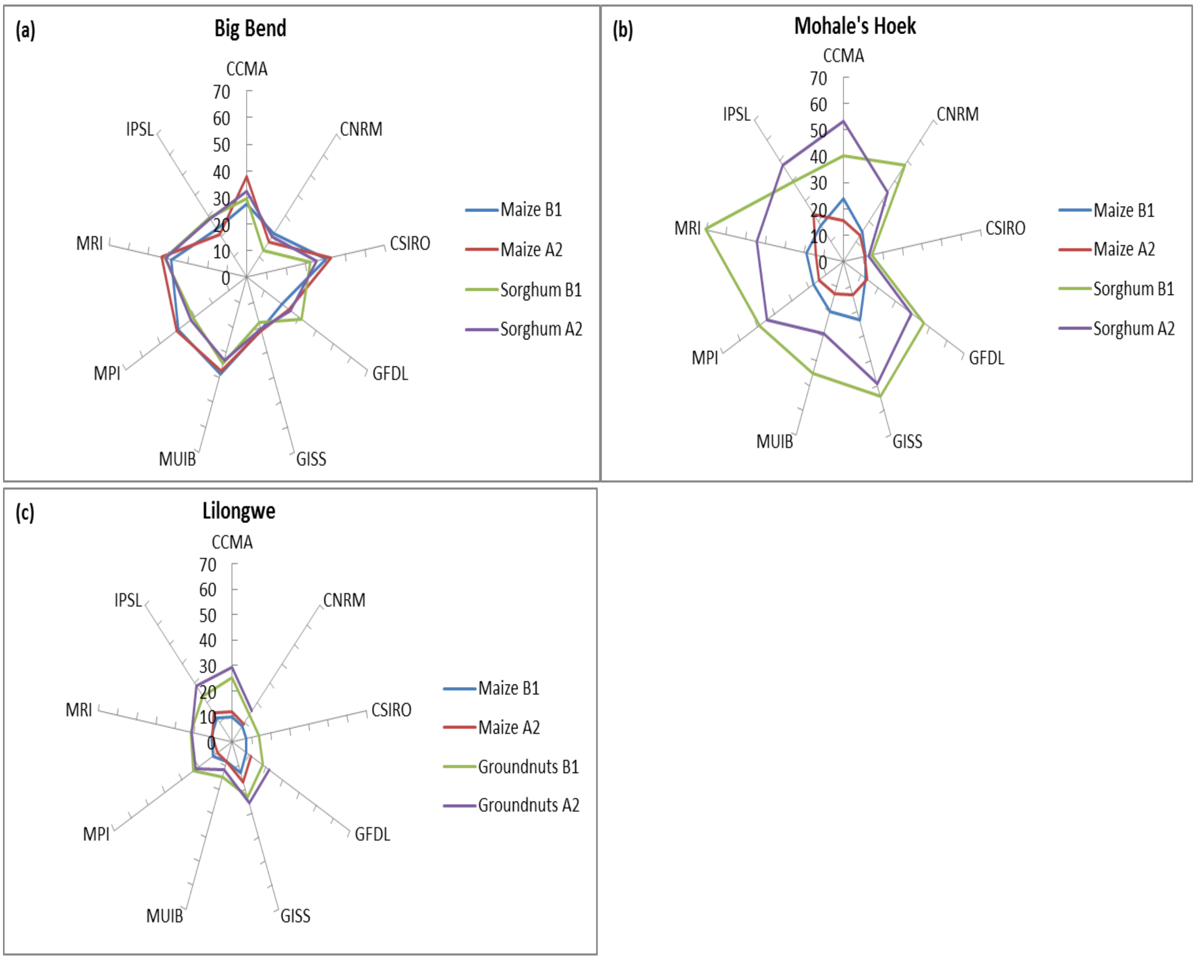

Fig 3 Mean percentage values of coefficient of variation. A measure of interannual variability of projected crop yields per locations and CO_2 emission scenarios B1 (low) and A2 (high), clustered by GCMs. GCMs references: see table 1.

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