Separate and combined effects of temperature and precipitation change on maize yields in sub-Saharan Africa for mid- to late-21st century

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1. Introduction

Process-based crop growth models are frequently used to simulate climate change impacts on agricultural crops in sub-Saharan Africa and many studies can be found in the literature for either the whole region (Jones and Thornton, 2003; Liu et al., 2008; Thornton et al., 2011; Folberth et al., 2012) or for individual African countries (Adejuwon, 2006; Thornton et al., 2009; Laux et al., 2010). These models compute important biophysical and biochemical processes, like photosynthesis, respiration and transpiration or the dynamics of carbon and water at the leaf-level (Tubiello and Ewert, 2002; Bondeau et al., 2007) and are therefore able to simulate the effect of increasing temperatures, changing precipitation and elevated atmospheric CO_2 concentrations on crop development and yields. Climate projections from general circulation models (GCMs) on air temperature, precipitation and annual atmospheric CO_2 concentrations are typically used as input for these models.

For sub-Saharan Africa GCM projections agree well in the level of average temperature increases between 3 to 4 K in the 2090s compared to the 1990s in the A1b projections, with deviations between seasons and regions (Christensen et al., 2007). The likelihood that the summer average temperature will exceed the current highest summer temperature on record is greater than 90% in West and East Africa in the 2050s and in nearly all parts of sub-Saharan Africa in the 2090s (Battisti and Naylor, 2009). In contrast GCM projections of changes in precipitation

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are more diverse and agreement on the direction of change is high only for eastern and southern Africa. Changes in precipitation in the Sahel and along the Guinean Coast are highly uncertain. Rainfall is likely to increase over eastern Africa and likely to decrease in southern Africa during winter and in western parts of southern Africa (Christensen et al., 2007). Analysing an ensemble of 14 GCM projections and three emission scenarios shows that the length of the growing season in the 2090s will be reduced by 5 to 20% relative to current conditions in most parts of Africa and by more than 20% in the Sahel and southern Africa (Thornton et al., 2011). As a result arid areas with a growing season length of less than 120 days are likely to expand by 5–8% in the 2080s for two emission scenarios (B2, A2) (Fischer et al., 2002). Additionally an increase in the number of extremely wet seasons in West Africa and East Africa by 20% and an increase of extremely dry seasons by 20% in southern Africa combined with an increase in the rainfall intensity is expected (Christensen et al., 2007).

Temperature and precipitation changes might limit crop growth and development to a different extent depending on the current growing conditions and the magnitude of climate change. Published studies either analyze the combined effect of precipitation and temperature changes on crops in a climate change impact study or highlight only the importance of one climate variable for crops. To our knowledge there is only one study separating the effects of temperature and precipitation on crop yields in Africa. In this statistical analysis for individual countries in sub-Saharan Africa Schlenker and Lobell (2010) show that impacts on aggregated crop yields due to temperature changes are much stronger (-38% to $+12\%$) than impacts due to precipitation changes (-3% to $+3\%$) for five different crops. Consequently they doubt that shifts in the distribution of growing season rainfall will outweigh temperature effects on yield. This is contradictory to findings from studies on the effect of rainfall variability on crops which highlight the importance of variable wet season starts and the occurrence of dry spells for crop yields (Barron et al., 2003; Sultan et al., 2005). Dry spells in the flowering phase at two semi-arid locations in East Africa are estimated to reduce potential maize yields by 15–75% depending on the soil water-holding capacity (Barron et al., 2003). Long periods of drought in low-rainfall years have already seriously affected Africa's agriculture and economy in the past (Sivakumar et al., 2005) and will remain a danger in water-limited environments. A recent survey among crop modeling experts suggests that in a crop model which investigates crop response to climate variability, precipitation variation has the greatest influence on crop yields (Rivington and Koo, 2011).

We test the hypothesis that both, changes in temperature and precipitation will have an important influence on crop yields in sub-Saharan Africa depending on the location, the current climatic conditions and the projected climate change. To analyze the effects of precipitation and temperature changes separately and in combination is important for understanding and modeling climate change impacts on agriculture. We also investigate the effects of changing precipitation variability on crop yields by varying the mean daily precipitation, the total wet season precipitation and the number of small and large precipitation events in our simulations. On the one hand this analysis helps to identify the limiting factors for agricultural production in different environments and prioritize adaptation strategies to climate change. The success of breeding programs and farmers in selecting drought- or heat-tolerant crop cultivars will depend on their knowledge about changing growing conditions and the severity of different types of abiotic stresses. On the other hand it enhances the understanding of temperature and water stress effects in the vegetation model in order to identify future research and model development needs. Comparing the separated effects of changing temperature and precipitation with the combined effect will also reveal if a combination of drought and heat stress would have an even more significant effect on maize yields as known from several studies with maize, sorghum, barley and various grasses (Barnabas et al., 2008). We choose maize (*Zea mays* L.) as an example crop as it is the most important food crop in sub-Saharan Africa in terms of harvested area.

2. Materials and methods

2.1. Climate data

The study area comprises all land area in Africa from 40° N to 40° S and from 20° W to 60° E. Daily precipitation data for the baseline climate 1991–2000, b-1995 hereafter, were taken from the WATCH Forcing Data (WFD) (Weedon et al., 2011). This data set combines monthly precipitation totals from the Global Precipitation Climatology Center (GPCCv4) (Rudolf et al., 2005; Schneider et al., 2008; Fuchs, 2009) and reanalysis data on day to day variability from the European Centre for Medium-Range Weather Forecasts database (ERA − 40) (Dee et al., 2011). Monthly mean air temperature and monthly cloudiness for the baseline climate b-1995 were taken from the Climate Research Unit database (CRU TS 3.0 1961–2005) (Mitchell and Jones, 2005).

Projections on daily precipitation, monthly mean air temperatures and monthly cloudiness for two future time periods were taken from nine GCMs for the A1b emission scenario from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset (Meehl et al., 2007). We choose these GCMs with available and complete data on daily precipitation, air temperature and cloudiness (see Appendix A) and the emission scenario projecting global warming of 2.8 K which is in the middle of the projections (1.8 K in SRES B1 and 3.4 K in SRES A2). The two projection periods are p-2060, represented by climate data in 2056–2065, and p-2085, represented by the time period 2081–2090.

For combining current and future climate into one time series, monthly temperature and cloudiness anomalies from each GCM were calculated for each year and month relative to current monthly climate data fields constructed from CRU TS 3.0 1961–2005 data after interpolating data to a resolution of $0.5° \times 0.5°$ and smoothing using a 30-year running mean (as described for CRU TS 3.1 in Heinke et al., 2012, p.3534). For temperatures, the anomalies were simply added and for cloudiness the relative changes were applied (for further details see Gerten et al., 2011). Future daily precipitation is generated from GCM projections according to climate experiments described below in order to study the effect of changes in the wet season length and wet season precipitation separately.

Daily mean temperatures in the baseline and projection periods are obtained by linear interpolation between mean monthly temperatures. Increasing atmospheric CO_2 concentrations can increase plant productivity if managed accordingly (Ainsworth and Long, 2005; Long et al., 2006). Given agricultural management deficiencies in sub-Saharan Africa, and to avoid mixing the effects of changing temperature and precipitation with possible effects of CO_2 fertilization on crop yields we here assume no effective CO_2 fertilization by keeping the atmospheric CO_2 concentrations constant at 370 ppm in our simulations.

2.2. Climate experiments

Generating synthetic climate experiments from GCM projections allows for analyzing the effects of changes in the wet season length and the wet season precipitation both separately and in combination with temperature changes in each grid cell. We are therefore able to test the sensitivity of the crop model to each agroclimatic variable separately.

In a first step, we calculate the relative change in the length and the precipitation amount of the wet season in p-2060 and in p-2085 compared to b-1995 for each grid cell from daily precipitation data of nine GCMs. The onset of the wet season is defined following Dodd and Jolliffe (2001) as a period of six consecutive days with at least 25 mm rainfall in which the start day and at least two other days are wet and no dry period of ten or more days occurs in the following 40 days. Accordingly, the wet season ends if there is no precipitation for ten consecutive days. In a second step we identify the GCM projecting the largest relative change in the length and total precipitation of the wet season for each grid cell after removing the outliers that deviate from the mean by more than two standard deviations to avoid extreme changes (see Appendix B). This procedure leads to rather negative precipitation projections for each grid cell, neglecting the large range of precipitation projections among the GCMs, but ensuring a reasonable level of changes in accordance with at least one GCM. These changes in wet season characteristics are applied to the daily precipitation series of the baseline climate (Fig. 1) both separately and in combination with corresponding temperature changes studying the effect of:

(1) changes in the precipitation during the wet season only (Cp),
(2) changes in the length of the wet season only (Cl),
(3) changes in the monthly mean temperatures only (Ct), and
(4) changes in all three agroclimatic variables (Cplt) on crop yields.

If the length of the wet season decreases, experiment Cl is realized by distributing the precipitation sum of the removed days equally to the remaining rain days in order to avoid altering the precipitation amount in the wet season. Consequently, the number of rain days decreases and the mean rainfall per rain day as well as the risk of extreme rainfall events increases. In contrast, mean rainfall per rain day decreases in experiment Cp, which reduces the risk of extreme rainfall events. The mean rainfall per rain day in experiment Cplt depends on the magnitude of both changes and on the precipitation amounts at the end of the wet season. The length of dry spells within the (shortened) wet season is not changed in any of these experiments, only the number of rain days and the number of small and large precipitation events (Fig. B-1 in Appendix B).

For the two future time periods in experiments Cp and Cl, monthly mean temperatures and cloudiness are kept constant over time with the baseline climate and are changing according to GCM projections in experiments Ct and Cplt. Temperature and cloudiness data were chosen in each grid cell from the GCM that was selected for precipitation projections in this grid cell. In total four climate experiments (three experiments for separated effects, one for combined effect) per grid cell are conducted.

2.3. Modelling the impact on agricultural vegetation

The impact of changing precipitation patterns and temperature increases on agricultural vegetation in sub-Saharan Africa can be simulated with the global process-based vegetation and agricultural model LPJmL (Sitch et al., 2003; Gerten et al., 2004; Bondeau et al., 2007). LPJmL is designed to simulate biophysical and biogeochemical processes as well as productivity and yield of the most important crops at daily time steps on global scale. The model is able to simulate maize and wheat yields globally (Fader et al., 2010) as well as crop yields of the major food crops in Africa (Waha et al., 2013). Water stress influences leaf growth (Bondeau et al., 2007) and root growth (Waha et al., 2013), which both affect the amount of harvestable biomass. Modifications of leaf and root growth are based on a water stress factor (WSF [0,1]) calculated for each day and accumulated for all days with water stress for root growth. WSF is calculated from the ratio of daily water supply, i.e. plant water uptake from the soil, and daily atmospheric water demand, i.e. potential evapotranspiration (Sitch et al., 2003). Temperatures below or above crop-specific optimal temperatures for photosynthesis (21–26 °C for maize) reduce the photosynthesis rate (Haxeltine and Prentice, 1996), and increasing temperatures accelerate plant development and therefore lead to lower grain yields.

The start of the growing period in all time steps is determined by the start of the rainy season from daily precipitation in b-1995 as described above (section "Climate data"). The length of the growing period is represented individually for each crop by the phenological heat units (PHUs) required to reach maturity. They are calculated from a multiple linear regression model between PHUs and climatic variables in each grid cell for each crop separately (Waha et al., 2013). For maize this relationship is rather weak but PHUs are in a reasonable range between 1880°Cd and 3640°Cd. Sowing dates and PHUs for maize are calculated once for climate conditions in the baseline climate and are kept constant over time. We do not allow for adaptation of sowing dates or crop cultivar in order to clearly separate the climate effects from possible adaptation measures. For the same reason only rainfed, single cropping systems are simulated as irrigation or growing a second crop if the growing season is long enough would influence crop yields considerably. The management intensity in a grid cell influences the attainable crop yield and is described by three parameters: the maximal attainable leaf area index, the maximal harvest index and a parameter scaling leaf-level biomass to field level as described in Fader et al. (2010). The management intensities per country were chosen to match observed production levels of FAO in the 5-year period 1999–2003.

For this study, maize yields were calculated by forcing LPJmL with the four climate experiments described above. The change in yield for each

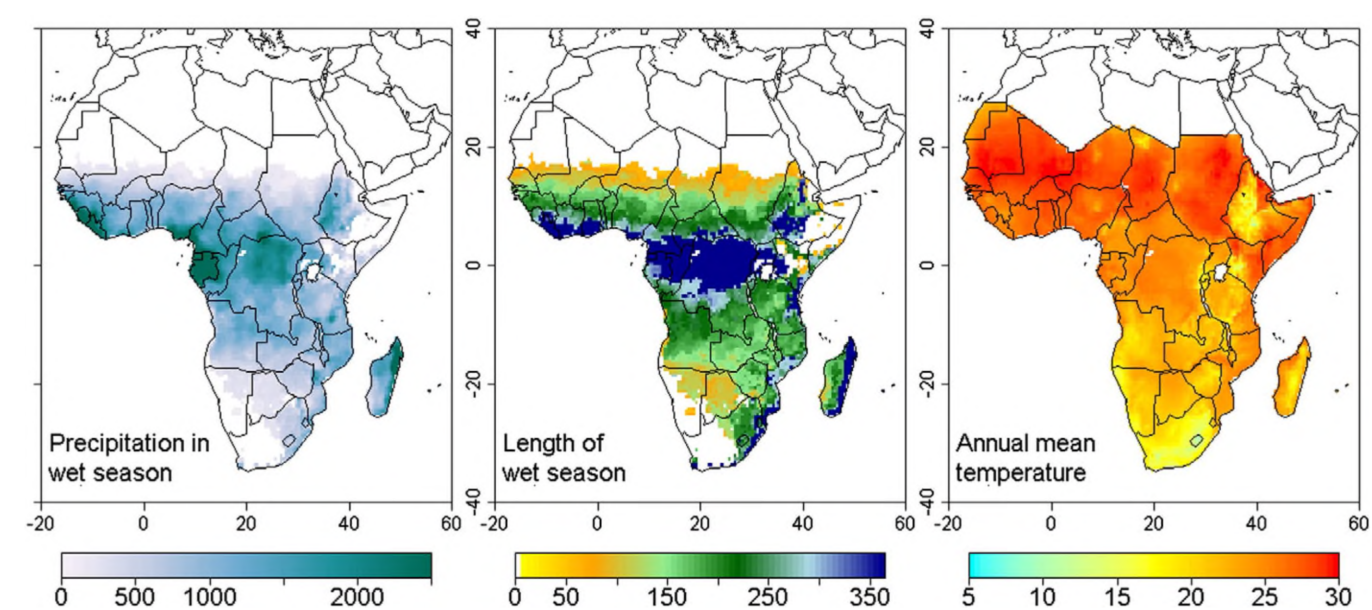

Fig. 1. Precipitation in the wet season (mm), length of the wet season (days) and annual mean temperature (°C) in b-1995 as calculated from daily precipitation and monthly temperatures. White areas are regions with a bimodal rainfall regime (eastern Africa) or desert areas (southern Africa) where no main wet season could be identified.

grid cell and the two projection periods compared to the baseline period is calculated as a result of changes in mean annual temperature only (ΔYI_{Ct}), wet season precipitation only (ΔYI_{Cp}), wet season length only (ΔYI_{Cl}) and in all three agroclimatic variables (ΔYI_{Cplt}) (see Appendix C). The methodology and expected results are summarized in Fig. 2.

2.4. Statistical analysis

We show results on the grid cell level and later also discuss differences between groups of grid cells with similar crop yield changes. We group the grid cells according to changes in maize yields due to the combined effects of temperature and precipitation changes in p-2060, applying hierarchical cluster analysis with the Ward's minimum variance method as a criterion for building clusters with the R function *hclust* (Murtagh, 1985). The distance between 1-dimensional clusters is calculated as the Euclidean distance. Each cluster can be described by the future crop yield changes, the initial climatic conditions in the baseline climate and the separated and combined effects of changes in temperature, the length and the precipitation amount of the wet season.

3. Results

We focus on results for grid cells with unimodal rainfall distributions, and if at least 0.1% of the grid cell area is used for maize production. We show changes in mean annual temperature, length of the wet season and precipitation during the wet season used as input data for the global dynamic vegetation model and impacts of these changes on maize yield in p-2060 and p-2085 relative to the baseline period b-1995. As crop yield changes are simulated using stylized climate scenarios for each grid cell, results are shown and discussed on the grid cell level and cannot be aggregated to country or regional level.

3.1. Changes in temperature, wet season length and wet season precipitation

GCM-projected daily precipitation data was analyzed with regard to the largest changes in the wet season precipitation and wet season length per grid cell after removing the outliers. The GCMs GFDL-CM2.1, GFDL-CM2.0 and CNRM-CM3 project the largest changes in the length and precipitation amount of the wet season in many parts of SSA, therefore the stylized climate experiments in almost half of the grid cells are based on climate change projections from one of these models. In the second half climate data from the remaining six GCMs is used in equal parts as input for the crop model. Most parts of sub-Saharan Africa experience decreases in both precipitation variables of up to 20% in both projection periods (Fig. 3). The wet season length and wet season precipitation decrease most severely in parts of the Sahel, southern Africa and central Africa. The spatial patterns of changes in the wet season precipitation and length of the wet season are very similar in most parts. However, in some regions the precipitation amount in the wet season decreases more than the length of the wet season, e.g. in West and East Africa between 5°N and 18°N. In contrast, the length of the wet season decreases more than the wet season precipitation in parts of Tanzania, northern Mozambique, Ethiopia or Angola. In 2–6% of all grid cells (depending on the projection period) the wet season length and wet season precipitation increase. Annual mean temperatures increase by 2–3 K in p-2060 and by 4–5 K in p-2085 whereas the increase is strongest in southern Africa and in the Sahel (Fig. 3).

3.2. Impacts on agricultural vegetation in sub-Saharan Africa

Temperature increases lead to crop yield reductions in the maize-growing regions of sub-Saharan Africa of 3–20% in p-2060, except for mountainous regions in South and East Africa and parts of western

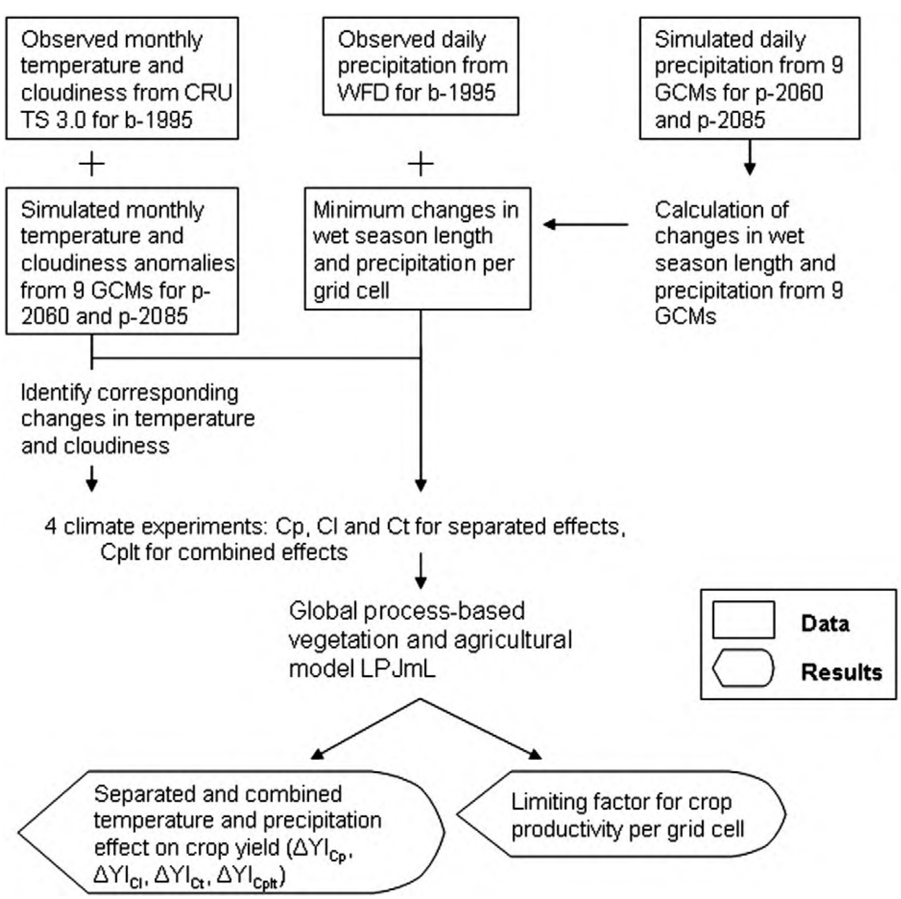

Fig. 2. Graphical abstract of the most relevant data, processes and expected results in this study.

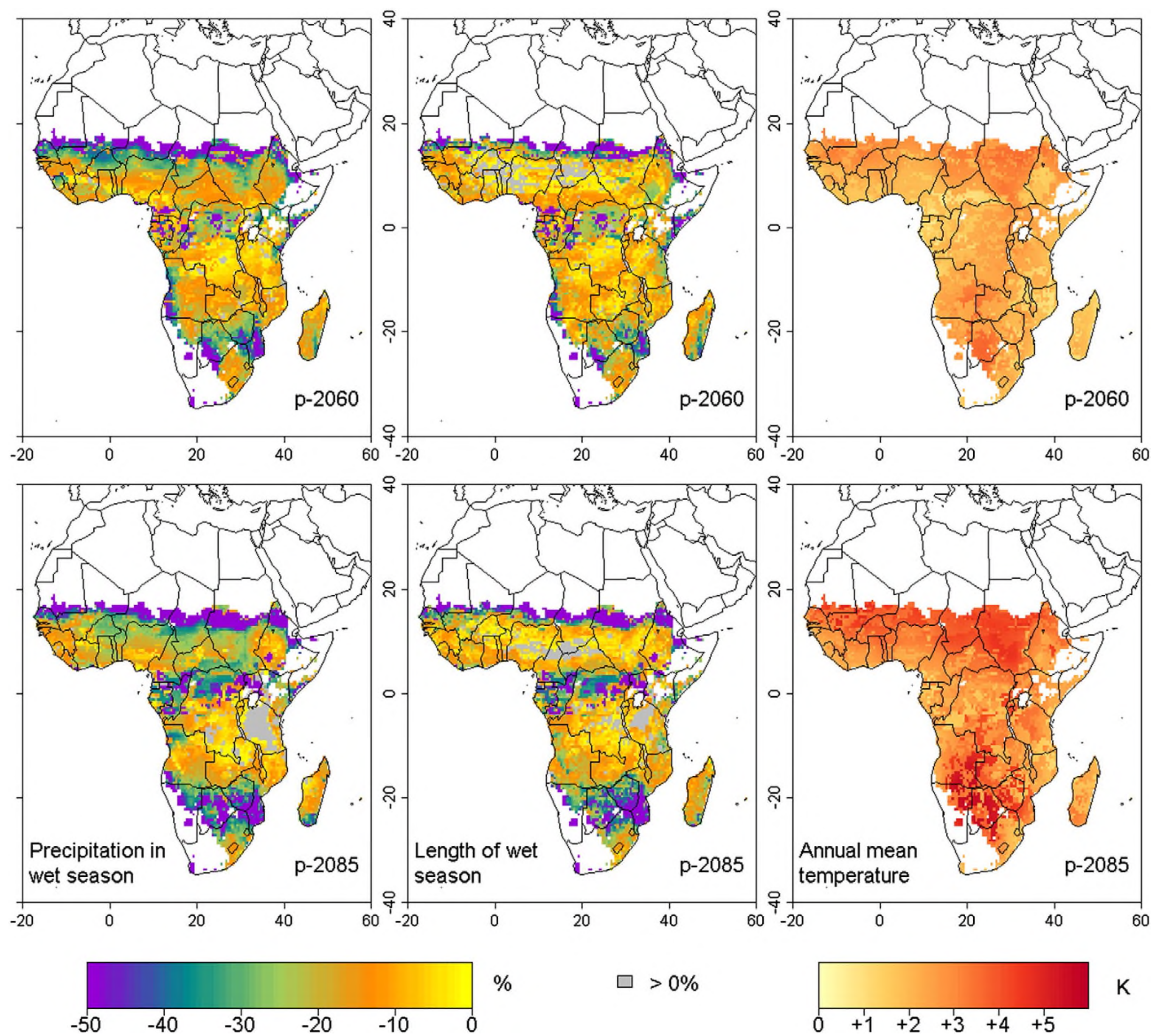

Fig. 3. Change in important agroclimatic variables according to GCM projections in p-2060 (top) and p-2085 (bottom) compared to b-1995 (from left to right): wet season precipitation, wet season length and annual mean temperature. The largest changes in the length and precipitation amount of the wet season per grid cell after removing the outliers and the corresponding temperatures are shown. Dark violet colors in the leftmost and middle panel indicate a reduction of 50% or more. White areas are regions with a bimodal rainfall regime (eastern Africa) or desert areas (southern Africa) where no main wet season could be identified.

Africa (Fig. 4). In most regions maize yields are lower in p-2085 than in p-2060. The effect of reduced precipitation on maize yields is even stronger in southern Africa, southern parts of Mozambique and Zambia, the Sahel and parts of eastern Africa, with yield reductions of up to 30% or even more. The effect of reduced precipitation in these regions clearly prevails over the effect of increased temperatures in p-2060 and p-2085. In all other parts, e.g. in Central and western Africa south of 13° N, the effect of increasing temperature is limiting because of very slight yield changes due to changes in wet season precipitation of −3% to +3%. In the mountainous regions of eastern and southern Africa, increasing temperatures lead to strong relative increases in maize productivity, making reduced precipitation the only limiting effect. The reductions in maize yields of 30% or more in southern Africa result from very different precipitation decreases of 50% and more in southern Mozambique and Zimbabwe, but only 10–20% in South Africa (Fig. 3). A shortening of the rainy season while conserving total wet season precipitation amounts (CI) does not affect maize yield negatively in most regions but partly leads to increasing crop yields. Maize yields in central Africa with an already long rainy season (>200 days) are not affected negatively by a shortened wet season at all.

4. Discussion

4.1. Understanding crop yield changes

The crop yield changes presented in Fig. 4 result from stylized climate experiments with rather large changes in the wet season precipitation and the wet season length and show the climate change effect on maize yields in each grid cell. They differ a lot between regions reflecting the differences in initial climate conditions and the corresponding crop's growing conditions as well as the magnitude of climate change. A cluster analysis allows for identifying groups of grid cells with similar crop yield

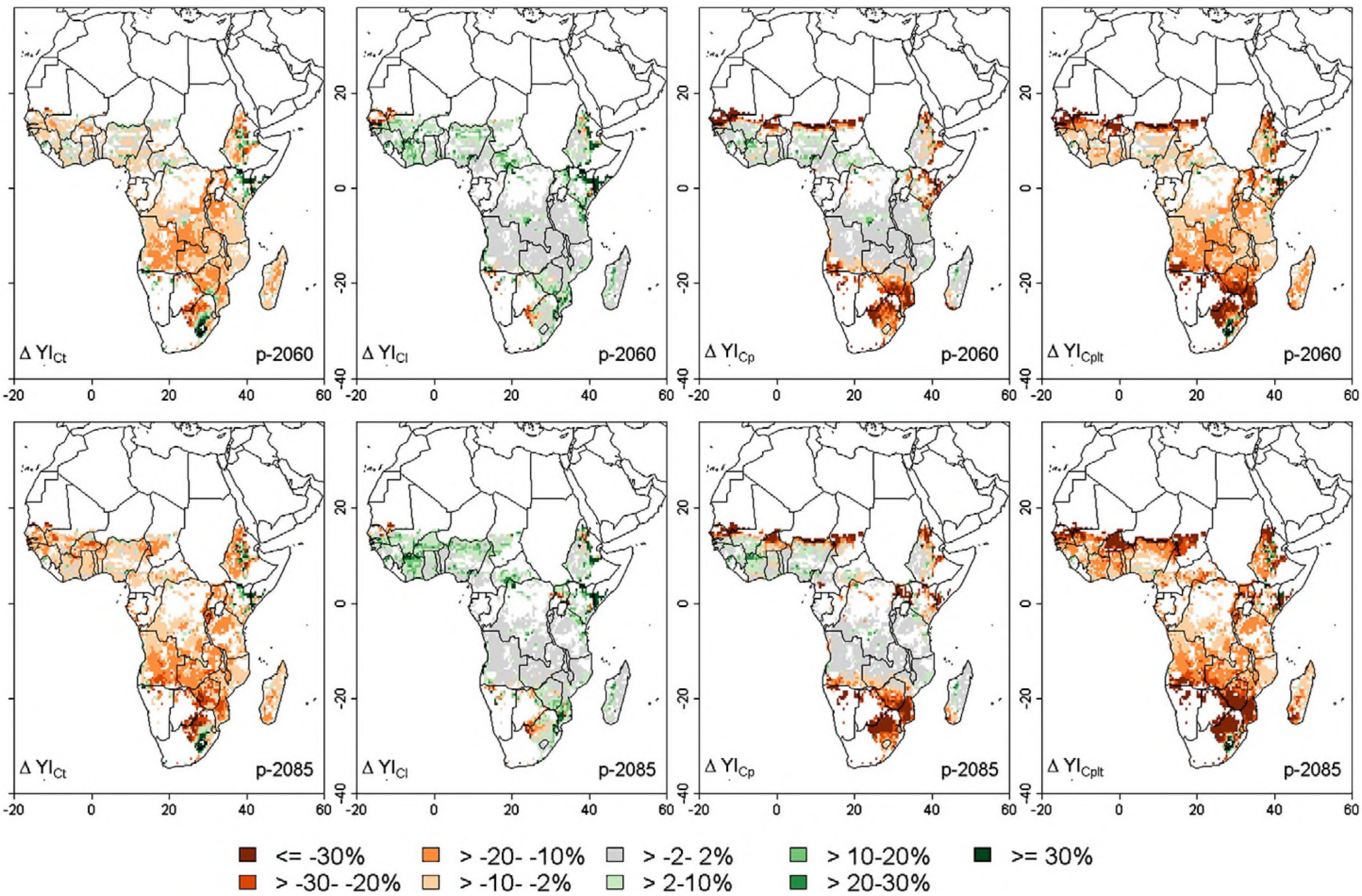

Fig. 4. Changes in rainfed maize yield calculated with LPJmL in p-2060 (top) and p-2085 (bottom), due to (from left to right) increasing annual mean temperature (Ct), shortened wet season (Cl), reduced wet season precipitation (Cp), and the combined effect from all three (Cplt). White areas in sub-Saharan Africa are excluded because the maize area is smaller than 0.1% of the grid cell area.

changes and for understanding the reasons for changes in crop yield under climate change. Fig. 5 shows these cluster groups and their initial climatic conditions in the baseline climate. The cluster groups differ in their future crop yield changes with boundaries at −33%, −10% and +6% (Fig. 6).

Grid cells attributed to group A are located in the Sahel, in southern Africa and in parts of eastern Africa. In this group strong negative effects on maize yields arise from climate change with crop yield decreases of at least 33% (Fig. 6). Mean annual temperature in the baseline climate is mostly above 28 °C, the wet season length is typically below 120 days and the wet season precipitation is often below 500 mm (Fig. 5, right side). High mean annual temperatures in the baseline climate and temperature increases of 2–3 K until 2060 indicate an increasing risk of extreme daily temperatures in group A. However, according to our results a reduction in the wet season precipitation causes a stronger decrease in crop yields than increasing temperatures in nearly all grid cells assigned to this group (Fig. 6).

In group B and group C moderate to slight negative effects result from climate change with maize yield changes between −33% to −10% and −10% to +6%, respectively (Fig. 6). Group C extends over parts of western Africa south of 13° N and of Central and East Africa. This group is characterized by high annual mean temperature (24–28 °C) and sufficient amounts of precipitation in the wet season (>750 mm). In most grid cells of group B or C the growing season is long and wet enough for the cultivation of maize in a single cropping system so that even considerable changes in the length of the wet season have little effect on yields. For the same reason the effect of a reduced wet season precipitation is less strong than the effect of increasing temperatures (Fig. 6). Temperature increase is slightly stronger in parts of southern Africa for group B (Fig. 3) leading to a stronger temperature effect on maize yields than in group C. A shorter wet season (Cl) only has a marginal effect on maize yields in group B and C as the growing conditions are not necessarily affected if the crop reaches maturity before the end of the wet season.

Group D is the smallest group and is characterised by positive effects of climate change on maize yields. Maize yield increases by at least 6% (Fig. 6) because increasing temperatures are favourable in an environment with an annual mean temperature between 13 °C and 15 °C and a long wet season (Fig. 5, right side). As also the mean rainfall per rain day is increased in the Cl experiment with a shortened wet season, the growing conditions improve leading to increasing maize yields in some regions.

In groups A to C with large to slight reductions in maize yields, the main limiting effect in each grid cell also determines the direction of yield change if all three effects are combined and negative effects from increasing temperature and changing precipitation exacerbate each other (Fig. 4 for e.g. Zimbabwe, southern Mali or Burkina Faso). In group D, in contrast the combined effect of changing temperatures and precipitation is positive following mostly from the beneficial effect of increasing temperatures.

Even slight to moderate yield changes might seriously endanger local food security if food production is already low or crop productivity is instable. The maize yields in all four groups range between 0.65 t/ha and 2.6 t/ha (Q5–Q95) and are evenly distributed over the groups therefore similar yield changes will have a very different effect on local food security. This becomes evident when comparing yield changes with an indicator of food security like the number of people undernourished in a country (FAO, 2011). Most parts of e.g. the Central African Republic belong to group C with only slight yield changes but

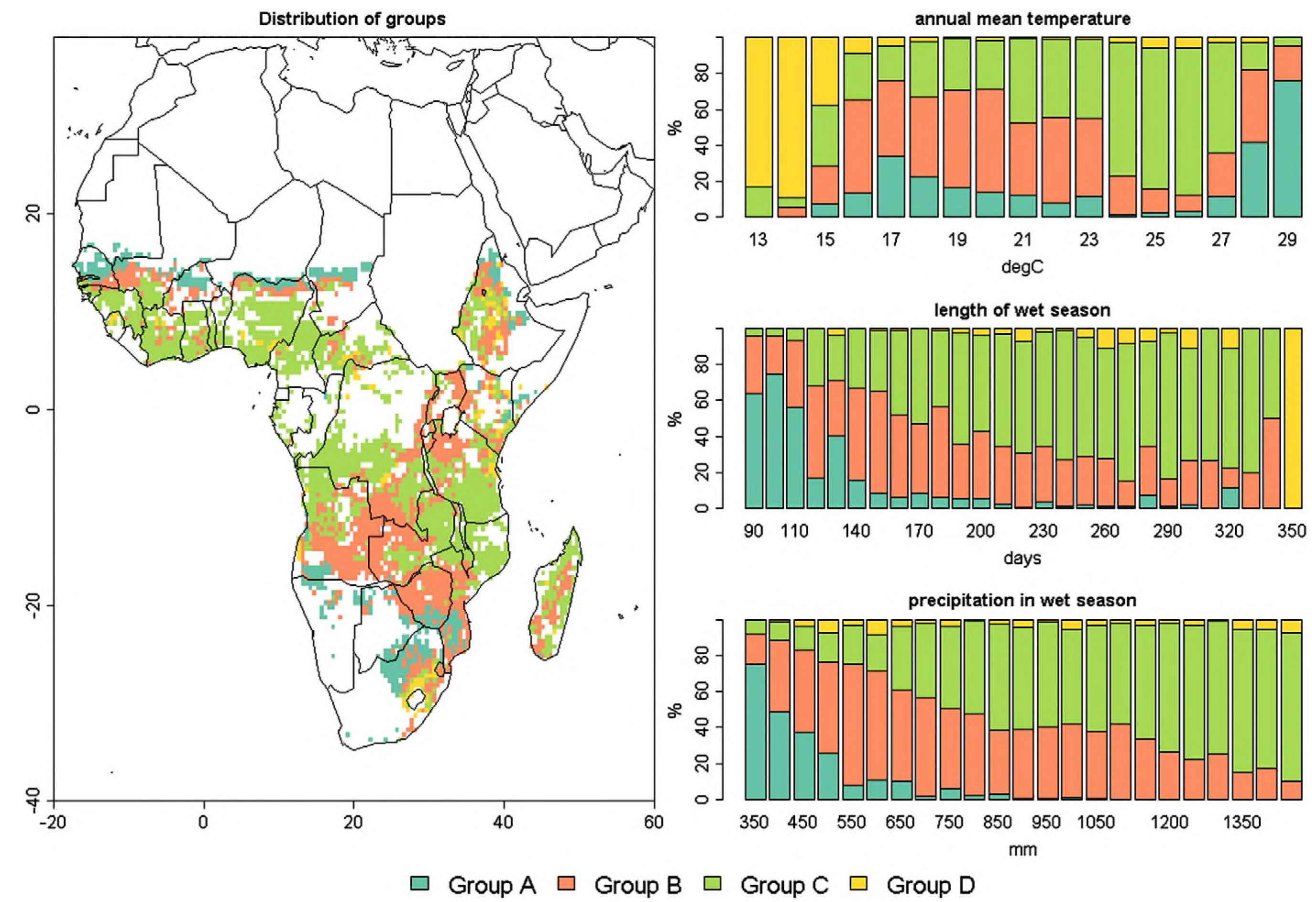

Fig. 5. Distribution and characteristics of four groups resulting from hierarchical cluster analyses of yield changes in p-2060 (Fig. 4, panel top right). White areas in sub-Saharan Africa are excluded because the maize area is smaller than 0.1% of the grid cell area. The stacked bar plots on the right side show the probability that grid cells within a group belong to a certain temperature class, wet season length class and wet season precipitation class. Labels at the x-axis are the lower class limits.

here 40% of the population was undernourished in 2006–2008 making the country much more vulnerable to yield reductions compared to Uganda with most parts of the country belonging to group B with higher yield decreases but less people undernourished today (22%).

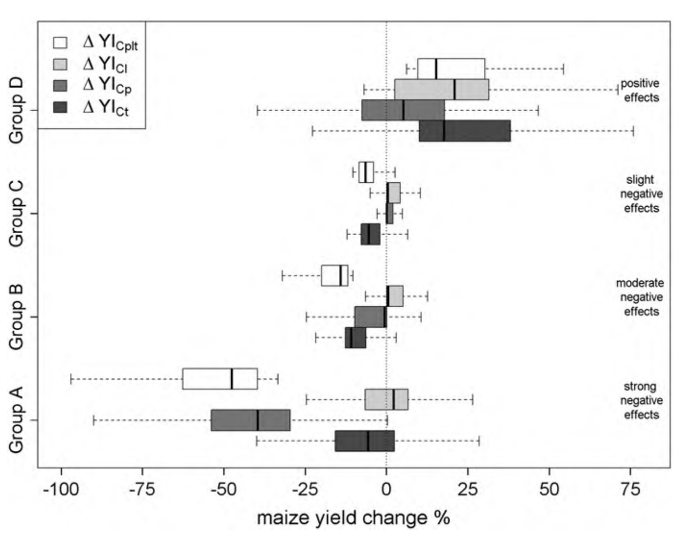

Fig. 6. Crop yield changes in p-2060 from the combined and separated effects of changing temperature (Ct), wet season precipitation (Cp) and wet season length (Cl) in groups shown in Fig. 5. Extreme data points that deviate from the borders of the box (Q25–Q75) by more than 1.5 times the interquartile range are not shown.

4.2. Uncertainty in GCM projections of precipitation

Although GCM projections agree on the level of median temperature increase, they project very different precipitation patterns in various regions of sub-Saharan Africa due to a large variety of model setting caused by the models' resolution and model physics, affecting e.g. the occurrence of convection or the vertical transport of moisture in the tropics (Lin, 2007). This influences the distribution of wet and dry days and the precipitation amount per wet day simulated in each GCM and in turn the severity of water stress in the growing season. There is some consistency between GCMs with respect to the projected increase of annual precipitation amount in East Africa and a drying in southern Africa. A consistent increase in the number of extremely wet seasons in West Africa and East Africa by 20% and an increase of extremely dry seasons by 20% in southern Africa combined with an increase in the rainfall intensity are also expected (Christensen et al., 2007). Most of the GCMs project excessive precipitation over much of the tropics and, associated with that, insufficient precipitation over much of the Equatorial Pacific (Lin, 2007). This double-ITCZ (Inter-Tropical Convergence Zone) problem together with another common bias of GCMs, the too strong persistence of tropical precipitation (Lin et al., 2006), might lead to poor representation of tropical precipitation patterns in some GCMs. An important element of tropical intra-seasonal variability and thus weather and climate forecasting between 15° N and 15° S, the Madden–Julian oscillation, is simulated nearly realistic from ECHAM5/MPI-OM and CNRM-CM3 (Lin et al., 2006). These models were chosen for our study as well and provide the climate input data in 26% of all grid cells in the studied region.

4.3. Limitations of modeling stress on crop growth and development

The global dynamic vegetation model LPJmL considers the effects of water stress on crop growth and development and temperature effects on the photosynthesis rate and length of the growing period (as described in the section "Modelling the impact on agricultural vegetation"). Results from previous studies on heat stress effects on crop yields in sub-Saharan Africa indicate that the Sahel and southeastern Africa are most affected by heat stress (Teixeira et al., 2013) and that maize yields are negatively affected in areas with an annual mean temperature above 25 °C because daily temperatures commonly exceed 30 °C. A yield loss of 10% per 1 °C of warming is possible in these regions (Lobell et al., 2011). These results agree well with the large yield reductions of at least 33% in grid cells in the Sahel and parts of southern Africa assigned to group A with an annual mean temperature above 28 °C and temperature increases of 2–3 °C in p-2060. It is however not clear to what extent maize yield is reduced because of shortened development phases, leading to reduced light interception in an accelerated life cycle and because of limited photosynthesis. This study does not consider several damaging effects of heat and water stress; on the other hand, the plants' ability to develop heat and desiccation tolerance is also omitted. This will be an important challenge of future research also with respect to projected changes in the occurrence of extreme events (Shongwe et al., 2009; Diffenbaugh and Scherer, 2011; Shongwe et al., 2011). The study of Barnabas et al. (2008) gives an overview of these damaging effects which are also important for the growth and development of cereals but not considered in the model. Among the most important effects are oxidative damage, modifications in membrane functions, denaturation of existing proteins, reductions in pollen germination ability due to high temperatures (>30 °C) and the delay or even depression of flowering due to limited water supply. For maize, daily temperatures above 33.5 °C and 38 °C were shown to reduce the kernel growth rate and the pollen germination ability, respectively (Barnabas et al., 2008).

The beneficial effect of elevated CO_2 concentrations on plant growth and above-ground biomass can be computed with LPJmL. This effect is not considered in the study, as its effectiveness, especially in nutrient-limited production systems that are coming in sub-Saharan Africa, is questionable without large additional nitrogen inputs (Long et al., 2006). The risk of crop damage due to increased temperature or water stress does not only depend on the magnitude of temperature and precipitation changes but also on the vulnerability of a region to these changes determined by current climatic conditions and farmer's management strategies for adaptation such as choosing an adapted sowing date or cropping system (Tingem et al., 2008; Laux et al., 2010). Selecting heat-resistant crop varieties is another adaptation option helping to reduce negative climate change impacts considerably e.g. in Mali, Butt et al. (2005) showed that heat-resistant maize varieties simulated with EPIC are less affected from climate change i.e. yields are reduced by 8.6% compared to a reduction of 11.2% without adaptation for a HadCM3 climate scenario. Applying water-harvesting techniques (Rost et al., 2009) and increasing rainwater productivity through conservation farming strategies (Rockström et al., 2009) might also lower the negative climate change impacts on crop yields considerably and are sometimes very cost-effective at the same time (Ebi et al., 2011). Future research on the effectiveness of various adaptive management strategies will therefore be important.

5. Summary and conclusions

We show that the importance of the agro-climatic variables temperature, wet season precipitation and wet season length for maize yields, varies in space depending on the initial climate limitations and the magnitude of climate change. Crop yields change considerably in regions with unsuitable or extreme growing conditions where even slight climate change results in strong relative effects on crop yields and in regions which are exposed to strong temperature and precipitation changes. The regions most vulnerable to temperature increases are southern Africa and parts of East and West Africa with annual mean temperatures of 18–24 °C which are exposed to annual temperature increases of 2–3 K leading to maize yield decreases of more than 20%. Parts of South Africa, Zimbabwe, Mozambique and the Sahel with higher annual mean temperatures above 28 °C are exposed to extreme daily temperatures but the temperature effect in the model is similar to the effect in regions with cooler temperature. This indicates that in the model increasing temperatures only affect the crop by shortening the growing season and limiting photosynthesis but that damage from extreme daily temperatures above 30 °C is largely underestimated in the model. The same regions are even more affected by precipitation changes as they have short (<120 days) and dry (<500 mm) growing seasons and reduced wet season precipitation leads to maize yield reductions of 30% or more. In the mountainous regions of South Africa and East Africa temperature increases are beneficial for maize growth and lead to increasing crop yields of at least 6%. These findings should be considered in drought and heat stress breeding programs and in studies on adaptation to climate change impacts. With climate change both, temperature and precipitation will change but determining the limiting effect helps to prioritize future research needs and to identify adequate crop varieties and adaptation options in different environments.

The model is sensitive to all three agro-climatic variables wet season length, wet season precipitation and temperature but reductions of crop yields mostly arise from changes in temperature and wet season precipitation. A shortened wet season with conserved total precipitation amounts does not affect maize growth in most parts of sub-Saharan Africa as maize is simulated to grow at the beginning of the wet season and mostly reaches maturity before the end of the wet season. Only in small parts of southern Africa and the Sahel with a wet season length not exceeding 100 days, maize yields are reduced because of a shortened wet season. The effect of a reduced wet season length would be much stronger in multiple cropping regions where the second crop is at higher risk to be influenced negatively from a shorter wet season. However, African farmers like many farmers in developing countries tend to be risk averse and might not take the risk of exposing themselves to a chance of yield loss in the second half of the growing period.

Authors' contribution

The contribution of the different authors was as follows: K.W. and C.M. conceived the original idea of studying the effects of changing precipitation variability on crops. K.W. expanded this into a study on separating the effects of temperature and precipitation on crops. C.M. prepared the daily precipitation files from 18 GCMs, which was the basis for analysing changes in the wet season length and wet season precipitation. All authors were involved in developing and discussing the methodology. K.W. prepared the precipitation input files, did the model runs, prepared the figures, did literature research and wrote the manuscript. All authors were involved in discussing the results and reviewing the manuscript several times.

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Appendix A. Global circulation models used in this study

Table A-1
Global circulation models used in this study (Randall et al., 2007).

Model name	Research group(s)	Country	Available reporting periods
CGCM3.1(T47)	Canadian Centre for Climate Modelling and Analysis	Canada	2046–2065, 2081–2100
CNRM-CM3	Météo-France / Centre National de Recherches Météorologiques	France	2046–2065, 2081–2100
CSIRO-Mk3.0	Commonwealth Scientific and Industrial Research Organisation, Atmospheric Research	Australia	2046–2065, 2081–2100
ECHAM5/MPI-OM	Max Planck Institute for Meteorology	Germany	2046–2065, 2081–2100
GFDL-CM2.0	U.S. Department of Commerce / National Oceanic and Atmospheric Administration / Geophysical Fluid Dynamics Laboratory	USA	2046–2065, 2081–2100
GFDL-CM2.1			2046–2065, 2081–2100
IPSL-CM4	Institut Pierre Simon Laplace	France	2046–2065, 2081–2100
MRI-CGCM2.3.2	Meteorological Research Institute	Japan	2046–2065, 2081–2100
PCM	National Center for Atmospheric Research	USA	2046–2065, 2080–2099

The Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset contains more than these GCMs. For this study eight GCMs were excluded because the data was not complete and one GCM was excluded because data on the precipitation amount in the wet season deviates from the mean by more than three standard deviations.

Appendix B. Method of generating stylized precipitation scenarios

Identifying the largest change in wet season characteristics

We first calculate the largest relative changes in total precipitation and length of the wet season in combination for each grid cell after excluding all outliers that deviate from the mean by more than two standard deviations to avoid overly emphasizing on extremes. We do this for the two time periods p-2060 and p-2085 separately as follows:

$$\min \left. \frac{P_{i,t}-P_{i,1995}}{P_{i,1995}}+\frac{L_{i,t}-L_{i,1995}}{L_{i,1995}}\right) \quad \forall \quad i=1,\ldots,9$$

with n = 9, where $P_{i,t}$ and $L_{i,t}$ are the precipitation in the wet season and length of the wet season, respectively at time t and for GCM *i*, $P_{i,1995}$ and $L_{i,1995}$ the precipitation in the wet season and length of the wet season in b-1995 and for GCM *i*.

We then assign the individual relative changes in both variables to the baseline climate of the WATCH Forcing Data (WFD) to obtain the daily precipitation for the climate experiments Cp, Cl and Cplt described

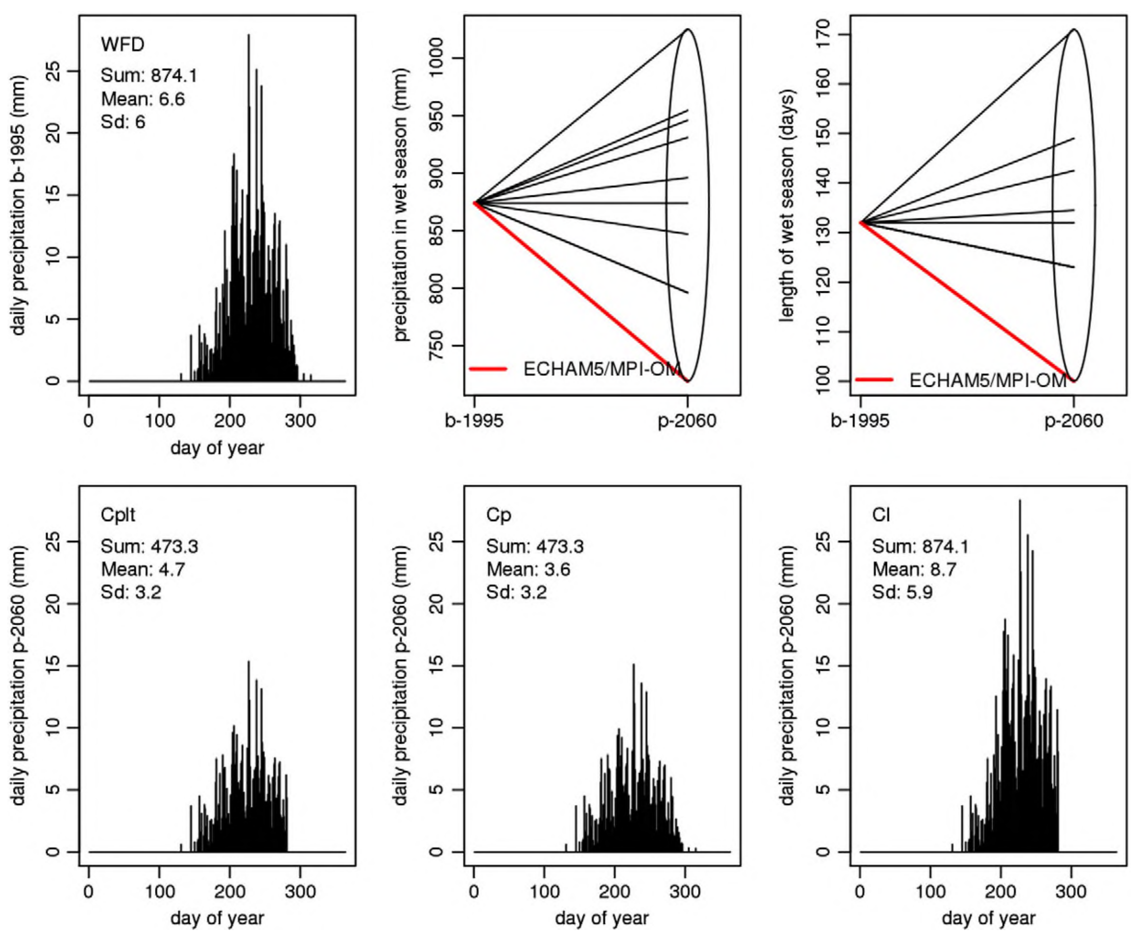

Fig. B-1. Daily precipitation changes in p-2060 for an example cell (Gambia: Lat = 13° 25′ N, Lon = 16° 75′ W). Top: Daily precipitation in b-1995 from WATCH Forcing Data (WFD) and projected changes in total precipitation and length of the wet season from nine GCMs. Bottom: Daily precipitation in p-2060 in the three climate experiments Cplt (combined), Cp (Changed precipitation), and Cl (Changed length).

in the methods section. Fig. B-1 shows an example for changes in daily precipitation in p-2060 for the GCM ECHAM5.

Overestimation of precipitation changes

It is assumed that assigning relative changes from GCM data to WATCH Forcing Data (WFD) as a common baseline climate is an adequate procedure, as this data lies within the range of baseline climates from all GCMs (Fig. B-2). However, the Kolmogorov–Smirnov test on the equality of distributions indicates that the total precipitation and the length of the wet season in b-1995 calculated from GCMs and from WFD differ significantly ($p < 0.001$) (Fig. B-2). Therefore, changes in p-2060 and p-2085 in total precipitation and length of the wet season may be overestimated if GCMs significantly underestimate actual values (Füssel, 2003).

The test statistic of the Kolmogorov–Smirnov test D gives an indication of the direction and strength of these differences. D is the maximum vertical deviation between two cumulative distribution functions, i.e. for the comparison between WFD and the GCM ECHAM5 with $D = 0.11$, the precipitation amount in the wet season is below ~1800 mm in ~98% of all grid cells in the GCM but only in ~87% of all grid cells in WFD (Fig. B-2, bottom panel right). ECHAM5 therefore significantly underestimates the precipitation amount in the wet season, just like three other GCMs in which D ranges from 0.08 to 0.33. Furthermore, seven out of nine GCMs always significantly underestimate the length of the wet season (Fig. B-2, bottom panel left, curves above WFD curve), with D ranging from 0.18 to 0.36. However, the quality of agreement to WFD varies regionally for all GCMs, e.g. the GCM GFDL-CM2.1 underestimates the precipitation amount in the wet season lower than 1000 mm but overestimates precipitation amounts between 1000 mm and 2000 mm (Fig. B-2, panel top right).

However, we assume that the risk to extremely under- or overestimate the wet season length and wet season precipitation in the future is reduced by removing GCMs as outliers if they deviate from the mean by more than two standard deviations.

Appendix C. Method for calculating crop yield and crop yield changes

The combined (ΔYI_{Cplt}) and separated effects of temperature, length of rainy season and total precipitation in the rainy season

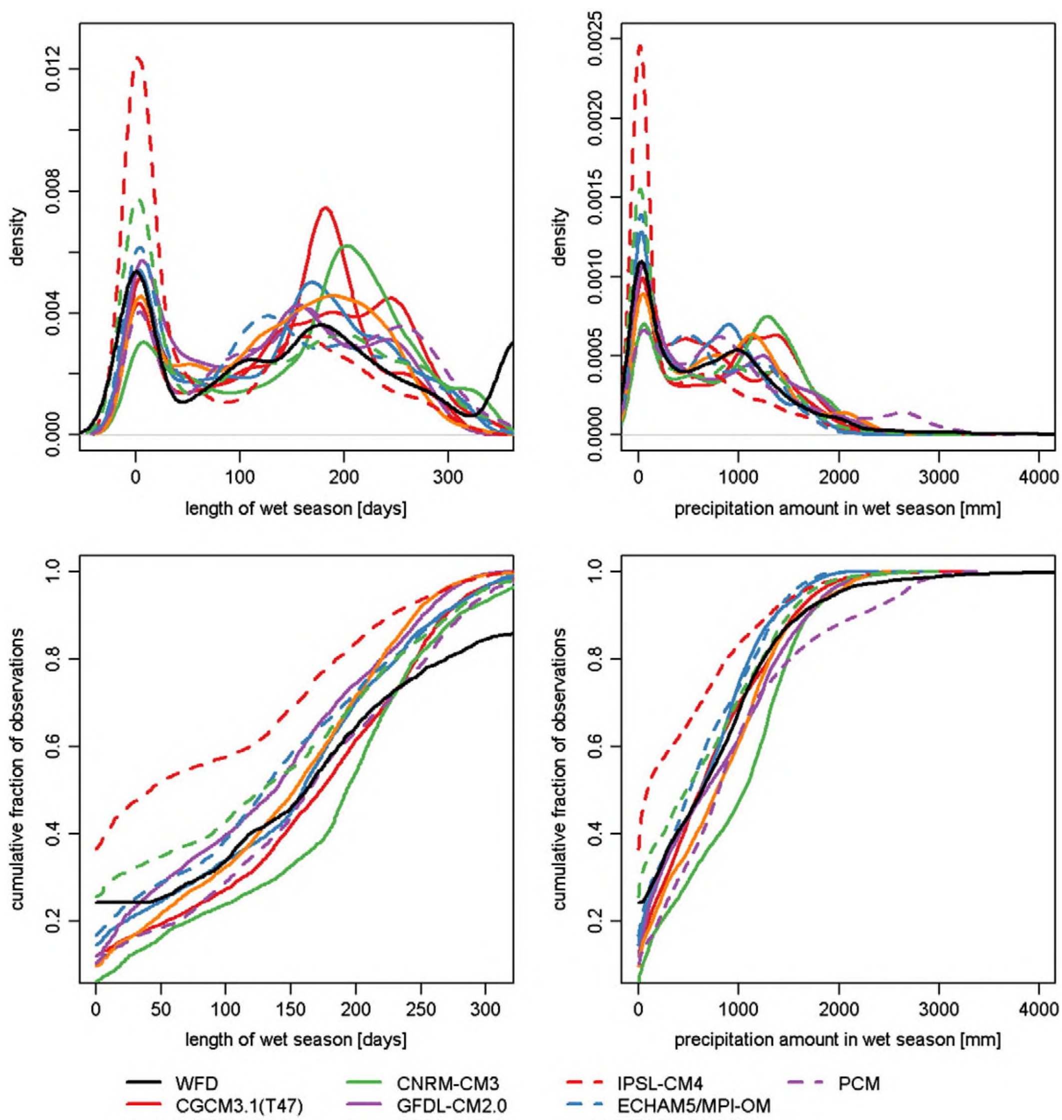

Fig. B-2. Distribution function (top) and cumulative distribution function (bottom) of the length of the wet season (left) and the precipitation amount in the wet season (right) in the baseline climate calculated from the WATCH Forcing Data (WFD) and from nine GCMs.

(ΔYI_{Ct}, ΔYI_{Cl} and ΔYI_{Cp}) on crop yield in each grid cell for two time periods are calculated as follows:

$$\Delta YI_{Cplt} = \frac{YI[P_t, L_t, T_t] - YI[P_{95}, L_{95}, T_{95}]}{YI[P_{95}, L_{95}, T_{95}]}$$
$$\Delta YI_{Cp} = \frac{YI[P_t, L_{95}, T_{95}] - YI[P_{95}, L_{95}, T_{95}]}{YI[P_{95}, L_{95}, T_{95}]}$$
$$\Delta YI_{Cl} = \frac{YI[P_{95}, L_t, T_{95}] - YI[P_{95}, L_{95}, T_{95}]}{YI[P_{95}, L_{95}, T_{95}]}$$
$$\Delta YI_{Ct} = \frac{YI[P_{95}, L_{95}, T_t] - YI[P_{95}, L_{95}, T_{95}]}{YI[P_{95}, L_{95}, T_{95}]}$$

where $YI[P_{95},L_{95},T_{95}]$ is the maize yield under precipitation (total precipitation in rainy season and length of rainy season) and temperature conditions kept constant at b-1995 level; $YI[P_t,L_t,T_t]$ the maize yield if the precipitation (total precipitation in rainy season and length of rainy season) and temperature conditions change over time (t is the 10-year period p-2060 or p-2085); $YI[P_t,L_{95},T_{95}]$, $YI[P_{95},L_t,T_{95}]$, $YI[P_{95},L_{95},T_t]$ are the maize yields under changed total precipitation in the rainy season, changed length of the rainy season and increased temperature, respectively.

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