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Projections of climate change impacts on potential C4 crop productivity over tropical regions

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ABSTRACT

Climate change impacts on agriculture could arguably be most critical for developing countries in tropical regions: their populations rely importantly on agriculture and climate-dependant resources, poverty limits their capacity to anticipate and adapt to climate change, and population increase already poses a serious challenge to food security in those regions. Current projections of climate change impacts on tropical crop yields, even though on average negative, remain largely uncertain: there is need for more consistent, large-scale, quantitative assessments.

In this study we use a newly developed agro-DGVM (Dynamical Global Vegetation Model including an explicit representation of croplands) driven by projections from several climate models and two SRES scenarios to evaluate climate change impacts on potential C4 crop productivity over Africa and India from 1960 to 2100. We specifically separate the effect of increasing atmospheric CO_2 levels. We perform transient simulations directly forced by climate model outputs: to preserve consistency in the analysis despite regional biases in climate models, we analyze yield change on a bioclimatic basis (using the Köppen classification) rather than on a geographical basis. We find that the potential productivity of one of the most important staple crops in those regions, millet, will overall decrease, on average over all models and scenarios, by −6% (individual model projections ranging from −29% to +11%). The bioclimatic analysis allows us to highlight the main climate drivers of these changes. The main impact is a moderate but robust temperature-driven yield decrease over Equatorial and Temperate Köppen zones; larger but much more inconsistent yield changes occur in Arid Köppen zones, reflecting the uncertainty in precipitation projections from climate models. The uncertainty in aggregated impacts reflects the uncertainty over these areas, underlining the need to narrow the uncertainty in precipitation projections over dry areas if more reliable agricultural impact assessments over tropical regions are to be provided. Our results are also consistent with the limited magnitude of the impact of increased atmospheric CO_2 levels on C4 crop yields described in the literature. While such climatic impacts further increase the challenge of achieving future food security in developing countries in the Tropics, most of these impacts can arguably be mitigated through adaptation measures and improved agricultural practices.

1. Introduction

One of the most direct impacts global climate change may have on human societies is the potential consequences on global crop production. Agriculture is indeed often considered as the most weather-dependant human activity (Hansen, 2002): mean climatic conditions are one of the factors, along with soil fertility and human management, determining mean crop productivity levels across the globe, and interannual variability in regional crop yields reflects regional climate variability (Lobell and Field, 2007). Therefore, anthropogenic climate change, as projected by the IPCC's Fourth Assessment Report (2007), has the potential to significantly impact global crop productivity. This is an additional strain on the global food system, which is already facing numerous challenges: in coming decades, crop production will need to increase greatly in order to keep up with population growth, economic development (e.g., shifts towards more carnivorous diets) and, possibly, increasing reliance on biofuels; furthermore it needs to do so with minimum environmental costs (e.g., deforestation). This is particularly true for developing countries in low latitudes, where most of today's nearly one billion undernourished people already live and where most of the population increase and economic development is expected to take place. For instance, Collomb (1999) estimate

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that by 2050 food production will need to more than quintuple in Africa, more than double in Asia, and nearly double in Latin America. Arguably, one cannot expect this increase in production to be achieved by simply expanding croplands (Griffon, 2006). In Sub-Saharan Africa for instance, expanding croplands to their maximum potential area while keeping crop yields constant would barely be sufficient to meet the projected increase in demand, while in effect resulting in complete deforestation. Increasing crop yields is thus a necessary strategy, and in this context, assessing the impacts climate change may have on crop productivity in those regions is of crucial importance.

There have been numerous studies on the impact of climate change on crop yields in tropical regions, mostly using climate models projections to drive process-based or statistical crop models. Climate change is generally expected to have detrimental impacts on low latitude crop yields, even under a moderate 1–2 °C local warming (IPCC WG II Summary for Policymakers, 2007). Over Africa in particular, crop yield changes are expected to be generally negative: in a recent review by Roudier et al. (2011), for instance, the meta-analysis of 16 studies over West Africa shows that, over all climate scenarios and models, countries, crops, etc., projected impacts are most frequently slightly negative (−10%). However, very large uncertainties remain between studies, with impacts ranging from −50% to +90%. This spread reflects the diversity of such impact studies, which often focus on different locations, and rely on different climate projections (models, scenarios), crops and crop models, downscaling techniques, time horizons, etc. Different studies may thus lead to different crop yield projections – in particular when climate projections used as input differ. This diversity makes it difficult to aggregate and upscale the corresponding projections to provide a consistent, spatially explicit impact assessment on the regional or continental scale.

There is thus a need to perform more consistent, large-scale and spatially explicit assessments of climate change impacts on crop yields. Such projections should also try to quantify, as much as possible, the associated uncertainties in crop yield changes. Some studies use extensive simulations with plot-scale process-based crop models over a continental domain to derive such large-scale projections (Jones and Thornton, 2003; Liu et al., 2008); however, such extensive analysis are costly and therefore usually rely on single climate models, not spanning the uncertainty in climate projections. Rather, some authors advocate the use of statistical modeling, based on observed relationships between current climate and yields at the regional scale that can easily be extrapolated out to the future with different climate models projections (Lobell et al., 2008; Schlenker and Lobell, 2010). More recently, the development of agro-DGVMs (Arneth et al., 2010), i.e., global vegetation models including a representation of croplands, offers another approach to provide large-scale, process-based climate impact assessments. Because such global land models are developed at the interface with climate models, they provide a convenient modeling framework to perform large-scale crop yield projections and can straightforwardly be driven by different climate models projections. Müller et al. (2009), for instance, use the LPJmL model (Bondeau et al., 2007), driven by projections from five climate models, to assess the effect of climate change on major crops globally by 2050.

In this context, we use a newly developed agro-DGVM, ORCHIDEE-mil (Berg et al., 2010a), which simulates tropical C4 cereals such as millet and sorghum, to project the large-scale impacts of climate change on yields in a tropical domain covering Africa and India, continuously from present to the end of the 21st century. To account for uncertainties in climate projections, the model is driven by climate projections for the A1B and A2 scenarios from, respectively, 7 and 5 climate models. We also specifically analyze the effect of atmospheric [CO_2] increase on yield projections. A specific aspect of our study is that we do not analyze yield projections on a geographical basis: rather, we analyze projected changes by bioclimatic zones. This allows us to directly use climate models outputs as forcing data to our vegetation model, despite regional biases in climate models. The methodology and the details of these simulations are presented in the second section. Section 3 presents the results; we discuss those projections in Section 4.

2. Models, data and methods

2.1. Model: ORCHIDEE-mil

ORCHIDEE-mil is an agro-DGVM developed at IPSL (Institut Pierre Simon Laplace) for tropical regions, i.e., a global dynamic vegetation model including a representation of tropical croplands (Berg et al., 2010a). It is built on ORCHIDEE (Krinner et al., 2005), the IPSL global vegetation model, and SARRAH, a crop model routinely used by agronomists over West Africa to simulate tropical cereals like millet and sorghum (Dingkuhn et al., 2003; Sultan et al., 2005).

ORCHIDEE simulates water, carbon and energy exchanges between the land surface and the atmosphere. It explicitly computes vegetation growth and can thus be forced by climate data to assess the impact of climate on ecosystems (e.g., Ciais et al., 2005). To represent global vegetation, ORCHIDEE uses 10 natural Plant Functional Types (PFTs), and two agricultural PFTs (C3 and C4). While the standard version of ORCHIDEE approximates croplands by grasslands, ORCHIDEE-mil includes, for the C4 cropland PFT, parameterizations and processes derived from SARRAH. ORCHIDEE-mil has been applied over West Africa and India, showing skill in simulating the large-scale interannual response of crop productivity to climate variability (Berg et al., 2010a,b; Berg, 2011).

Crop phenology in ORCHIDEE-mil is driven by water availability and temperature: depending on soil water content variations, a rainy season is defined, during which sowing is allowed and is based on a threshold rainfall value. Photosynthesis follows the scheme developed by Collatz et al. (1992) for C4 plants. Crop growth and development then follows the scheme presented in Berg et al. (2010a). In particular, the length of the different developmental stages and total cycle duration are computed in thermal time (i.e., sums of temperature to be reached). Although further model development will enable having different cultivars with different thermal time requirements over different locations, in the simulations presented in this study only one cultivar is used, with a thermal time requirement of 1560 degree·day (around 90 days at an average temperature of 28 °C and with a base temperature Tb of 11 °C). One should note, however, that this fixed thermal duration results in varying actual temporal durations, depending on local temperatures. In addition here, because our study domain is larger than the West African domain initially analyzed in Berg et al. (2010a) and encompasses different climatic zones, a parametrization is added to the model to allow Tb to vary in regions where temperatures are lower. Over a given pixel, an estimated cycle temporal duration (i.e., the number of days necessary to reach 1560 degree·day) is computed based on the difference between the local mean annual temperature and the initial Tb (11 °C); if this duration exceeds 150 days, Tb is reduced, by the necessary number of degrees. This crude parametrization avoids simulating unrealistically long crop cycles in colder regions, and reflects to some extent the adaptation of local cultivars to climate. Finally, in climatic zones where water availability is not limiting (i.e., where precipitation occurs all around the year, e.g., equatorial areas), several cycles may take place during the year. In such cases we show as result, except when otherwise stated, the mean yield over the different cycles.

Table 1
Climate models and scenarios used to force ORCHIDEE-mil in this study. A full description of those models can be found at http://www-pcmdi.llnl.gov/ipcc/model_documentation/ipcc_model_documentation.php.

Climate model	Simulations with the A1B scenario	Simulations with the A2 scenario
BCCR	Yes	Yes
MIROC MEDRES	Yes	Yes
MIROC HIRES	Yes	No
CSIRO3.5	Yes	Yes
GISS AOM	Yes	No
IPSLCM4	Yes	Yes
INMCM	Yes	Yes

It is important to note that ORCHIDEE-mil only simulates the potential climatic yield from a modern cultivar: it does not account for other non-climatic yield-reducing factors, such as soil fertility limitation, pests or diseases. Therefore, when compared to actual yield data such as those from the FAO (Food and Agriculture Organization of the United Nations), simulated yields are in most cases overestimated (Berg et al., 2010a); however, this bias can be considered constant over time, and the model correctly captures the large-scale (i.e., country-level or regional) yield variability in response to climate (Berg et al., 2010a; Berg, 2011). The implications of this bias for the present study will be discussed in the last section.

2.2. Climate data

Monthly outputs from transient simulations over the 20th (20C3M, 1961–2000) and 21st (2001–2100) centuries were retrieved from the PCMDI archive (Program For Climate Model Diagnosis and Intercomparison) for several climate models and scenarios from CMIP3 (the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 multi-model dataset). We aimed at using as many climate models as possible, in order to span the uncertainty in climate projections; however, the availability of the various climate variables limited, in effect, the number of climate models that could be used: 7 models for the whole 1961–2100 period with the A1B scenario, and 5 for the same period with the A2 scenario (these 5 models being a subset of the 7 first ones – see Table 1). When forced by monthly data, ORCHIDEE uses a weather generator to temporally disaggregate the data (Richardson and Wright, 1984; Friend, 1998). The monthly variables used are: precipitation, number of rainy days, 2-m temperature, 2-m minimum and maximum temperatures, surface specific humidity, 10-m wind, cloud cover. The number of rainy days per month was not available at a monthly time scale in the PCMDI archive: it thus had to be recomputed for the different climate models. To do so, the number of rainy days per month (daily rainfall greater than 1 mm) was computed for the different climate models for time periods over which the models outputs were available at a daily time step (i.e., 1961–2000, 2046–2065, 2081–2100). Then, for each pixel, for each month, the number of rainy days was linearly interpolated between the mean values of the different time periods.

To allow comparing the results of the different simulations more easily, all climate model outputs are regridded to a $2.5^\circ \times 2.5^\circ$ resolution.

2.3. Methods

2.3.1. Simulations

ORCHIDEE-mil is forced by the datasets described above over a tropical domain including Africa and India (30°S–35°N; 20°W–90°E), two regions which are the largest producers of millet and where the model has been used before (Berg et al., 2010a, 2010b; Berg, 2011):

- Transient runs are performed over 1961–2100, with a 30 years spin-up performed on the first year of simulation (1961) to initialize soil water content. Historical runs (over 1961–2000) are performed with historical CO_2 values. Runs for the 21st century are performed either with the changing CO_2 concentrations from the corresponding scenario over 2000–2100, or with CO_2 levels kept constant at their 2000 value.

Because cropland area projections are intrinsically uncertain and because we are interested in the potential of change in crop productivity over the whole study domain, no cropland distribution map is prescribed in our simulations: croplands are simulated everywhere over the study domain. In this theoretical framework, and since we are only interested in crop yield change, no other type of vegetation is simulated here. Given that, in a more realistic case with prescribed natural vegetation, croplands in the model would be simulated on a separate tile from natural vegetation, this simplified approach has little consequence on the simulated land surface hydrology of croplands and subsequent plant growth.

2.3.2. Output analysis

Climate models have important regional biases, for different climate variables. This is particularly true for precipitation patterns in the Tropics: Cook and Vizy (2006), for instance, show that coupled climate models poorly represent the mean climatology of the West African monsoon. It is thus difficult to analyze the projected impacts of climate change on crops on a geographical basis (e.g., yield change in a given country): because of these biases, aggregating simulation outputs by geographical units (countries, or sub-regions) might lead to spurious results. For instance, if in a given climate model the simulated West African monsoon is too weak and rainfall does not propagate inland enough, aggregating ORCHIDEE-mil's subsequent outputs over Sahelian countries (Niger, Mali, Senegal, etc.) will in effect result in considering pixels that do not correspond, in the model, to the simulated Sahel, but to a simulated desert area. This will lead to irrelevant results, in particular if one analyzes projected yield changes in these countries and compare these results across different models with different biases. Therefore, raw climate model outputs are usually not used to drive large-scale impact assessment models: most studies rely on the "anomaly method" – that is, simulated climate changes are added to a baseline observed climatology. This method is almost systematically used for large-scale assessment of future climate change impacts on agro-ecosystems driven by climate model projections, whether with statistical models (Schlenker and Lobell, 2010) or with process-based models (Cramer et al., 2001; Jones and Thornton, 2003; Scholze et al., 2006; Müller et al., 2009). The rationale for this method is that it removes the mean biases from the climate model outputs: therefore outputs from the vegetation model can be analyzed on a geographical basis. It is arguably the only direct method to get around large-scale climate model biases for impact assessments. However, it is not completely satisfactory: the climate change anomalies that are added to the observed climatology may not be geographically consistent with the baseline climatology. For instance – following the same example as above – precipitation changes over the "geographical" Sahel, in a given climate model, might in fact correspond, in the model simulated climate, to precipitation changes over the Sahara – if the West African monsoon is too weak – or over the sudanian domain – if the monsoon is too strong.

In this context, to analyze our simulations we adopt a bioclimatic approach instead: simulation outputs are aggregated not by geographical units, but by bioclimatic regions. This allows us

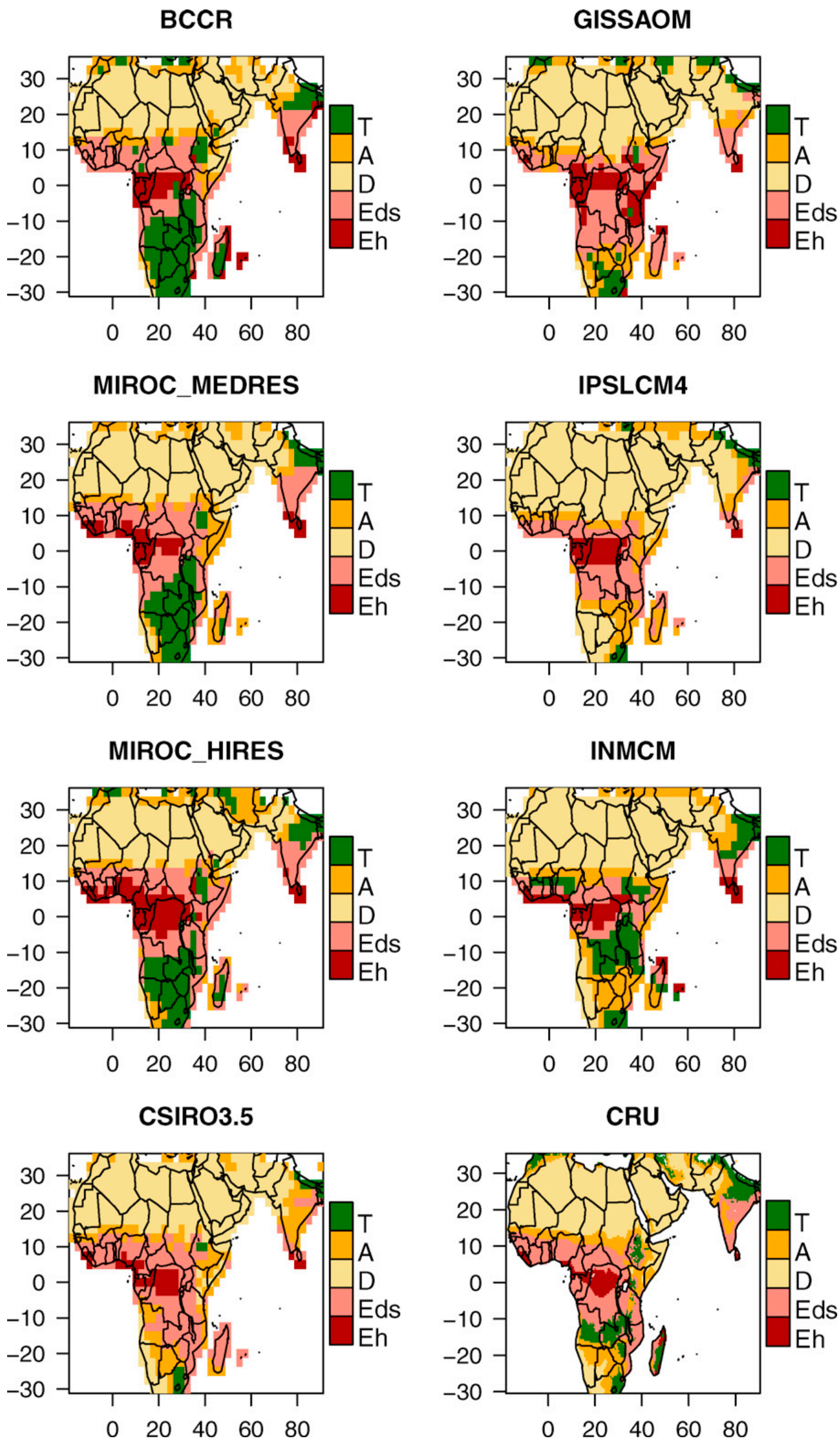

Fig. 1. Simplified Köppen classification, over the study domain, for the 7 seven climate models used in this study, defined from the monthly outputs over 1961–2000 from the 20th century runs stored at the PCMDI archive. The bottom right panel is obtained from the CRU monthly data over 1961–2000 (Mitchell et al., 2004). T, temperate; A, arid; d, desert; Eds, equatorial with dry season; Eh, equatorial fully humid.

to use climate model outputs directly to drive ORCHIDEE-mil, despite regional climate biases, while not relying on the "anomaly" method. Because of the differences in the mean simulated climate in various GCMs, the corresponding geographical regions are not the same across the different models; however, they share broady similar climatic conditions. Because they result from the same general physical processes in the climate models, their projected evolution can be compared across different GCMs. Such a method thus provides a more physically consistent assessment of crop yield potential changes over current bioclimatic zones. Moreover, despite the use of uncorrected climate models outputs, this approach also allows one to provide an aggregated estimation of climate change impacts over the study domain that remains consistent with the observed climate, by weighed-averaging the crop productivity changes over the different bioclimatic zones by the current, observed proportions of these same zones (Fig. 1, bottom right panel).

In our study the bioclimatic regions are defined according to the Köppen bioclimatic classification (Kottek et al., 2006). The definitions are based on threshold values and seasonality of monthly temperature and precipitation, taking into account the interactions between both variables (see Kottek et al., 2006 for more details). We acknowledge that other climate classification could be considered, such as the Thornthwaite classification (Feddema, 2005). The rationale for adopting the Köppen classification in this study is that it is meant to empirically reflect biome distributions, thus corresponding to different climatic constraints and different plant behaviors. Given the large number of climate types (31) in the complete Köppen classification, we only consider here the 7 most generic types: when restrained to the simulation domain, these types correspond to Equatorial fully humid zones, Equatorial zones with a dry season, arid zones, warm temperate zones (simply called Temperate zones in the following), and Desert zones (Fig. 1). The simplified Köppen types are defined for each model over 1961–2000. One may note the differences across GCMs, and the errors when compared with observations (CRU data from Mitchell et al., 2004), even with a simplified classification (Fig. 1). This illustrates the regional biases in the simulated climate of these models. For instance, India is simulated as mostly an 'Arid' or 'Desert' zone in the IPSLM4 model, whereas it is mostly an 'Equatorial with dry season' zone in observations (Fig. 1). Gnanadesikan and Stouffer (2006) have used a similar simplified Köppen classification to evaluate coupled climate models.

To analyze the transient simulations and evaluate future yield changes, we simply average simulated yields every year over each climatic zone in each model, keeping the present-day location of this climatic zone constant in this model. In other words, for each climatic zone, yields are averaged over the same pixels every year – bioclimatic zones are not redefined over time. Because we perform transient simulations, we are able to evaluate impacts on any time horizon. Here we mainly focus on long-term yield changes (i.e., for 2070–2100); we also present results for the shorter term (2020–2050).

3. Results

3.1. Climate change

Fig. 2 shows the projected climate change for the different climate models and climatic zones, by 2070–2099. Climate models consistently project increased temperatures over the study domain, between +2.1 K and +4.7 K across models, zones, and scenarios (Fig. 2). There is more variability between climate models than between Köppen zones: over our study domain, the increase in temperature within one model is rather homogenous – at the exception of desert regions, which in general warm more – so that in one model all Köppen zone experience a broadly similar warming. Although the relationship is not linear, the difference in temperature increase across climate models tends to reflect the different climate sensitivities of the GCMs. Models with high climate sensitivities, such as IPSLCM4 and MIROC-HIRES (respectively +4.3 and +4.3 K for doubled atmospheric CO_2 concentration) show the largest increase in temperature, whereas models with low sensitivities, such as GISS-AOM and INMCM (respectively +2.65 and +2.1 K) show lower warming over the study domain.

By contrast, the projected relative changes in precipitation remain small (most of the time below 10%) and largely inconsistent across models (in sign and amplitude) for all Köppen zones. Moreover, they are not always significant when compared to interannual variability. This is consistent with the well-know result that rainfall projections on tropical land are mostly inconsistent across climate models (e.g., Douville et al., 2006). Over the study domain, this is particularly true for West Africa (Cook and Vizy, 2006; Christensen et al., 2007). There are no obvious relationships between warming and precipitations changes over the different zones.

Warming is only slightly more pronounced under the A2 scenario (Fig. 2) than under the A1B scenario, by roughly 1 K; changes in rainfall, on the other hand, are insensitive to the emissions scenario (Fig. 2).

3.2. Change in simulated yields

Fig. 3 shows for each climate model and Köppen zone, the projected long-term yield change by the end of this century (2070–2099), as well as the shorter term yield change (2020–2049), compared to the 1970–1999 baseline, for each scenario. In those simulations, atmospheric CO_2 increases (according to the corresponding scenario).

Under both scenarios and on both time horizons, projected yield changes follow the same general pattern. Yield changes are consistently negative in both Equatorial zones (fully humid and with a dry season), and to a lesser extent, in the Temperate zone. The largest long-term yield decreases remain around −20%. On average, the projected long-term decrease is strongest in the "Equatorial fully humid" zone (−16.3% under the A1B scenario, −18.7% under the A2 scenario). Relative yield changes in "Arid" zones, on the other hand, are larger, but also more inconsistent across climate models. For instance, long-term impacts range from −44% to +56% under the A1B scenario. It has to be noted that, although larger in relative values, the projected yield changes in those areas remain more modest in absolute terms, because absolute simulated yields are lower: for instance the decrease in Fig. 3d in the IPSLCM4 simulation corresponds to an absolute decrease of −89 kg/ha.

Climate change impacts on yields remain smaller on the short term than on the long term, but impacts are already discernible by 2020–2049. For instance the average yield decrease on the "Equatorial fully humid" zone is −6.8% under the A1B scenario (−6.1% under the A2 scenario). However, yield changes by 2020–2049 are not always significant, in particular over Arid areas (Fig. 3c).

As mentioned in Section 2.3.2, an aggregated impact can be estimated over the whole study domain by weigh-averaging yield changes in the different Köppen zones by their observed, present proportions (see Fig. 1, bottom right plot). The projected long-term yield change over the whole domain under the different climate model projections then ranges from −27% to +11%, with a mean inter-model value of −5%, under the A2 scenario (−29% to +11% under the A1B scenario, with a mean value of −7%).

Finally, Fig. 4 shows the changes in yield interannual variability (measured by the coefficient of variation of yields averaged over each Köppen zone). One can note that, except for IPSLCM4, the changes in mean yield over the Arid Köppen zones reported above are associated with opposite changes in variability: in models where mean yields increase (decrease), interannual variability decreases (increases). Although changes in variability may be significant for other Köppen zones, no such relationship appears.

3.3. Climatic drivers of simulated yield changes

Analyzing yields on a bioclimatic basis allows us to highlight more easily the main first-order climatic drivers behind those changes. Fig. 5 shows the average yield changes as a function of mean climate change for each Köppen zone. We focus on long-term changes in order to maximize the climate change signal. In Equatorial zones and in the Temperate zone, the decrease in yields appears relatively proportional to the increase in temperature. In

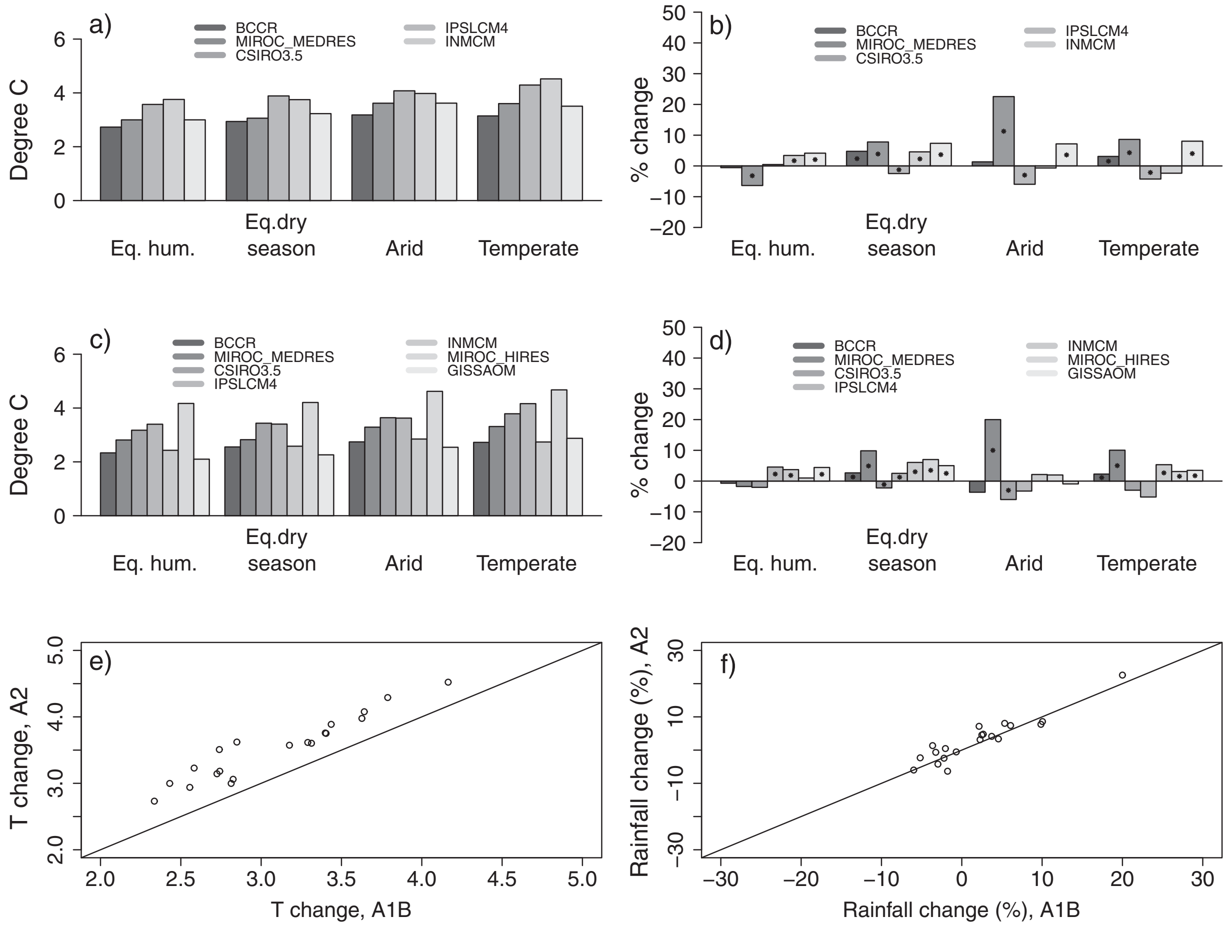

Fig. 2. (a) Average temperature change between 2070–2099 and 1970–1999 over the different Köppen zones and climate models, for the A2 scenario; all changes are significant compared to interannual variability; (b) average relative change in annual precipitation between 2070–2099 and 1970–1999 over the different Köppen zones and climate models, for the A2 scenario. Dots indicate changes that are significant at the 5% level; (c) and (d) same as (a) and (b) but for scenario A1B. (e) Comparison between the data from (a) and (c), for the 5 climate models for which simulations were performed both for the A1B and A2 scenario (5 models × 4 zones = 20 points); (f) same as (e), but for precipitation changes.

Arid zones, on the other hand, yield changes appear mostly driven by the change in rainfall.

Because cycle duration in the model is computed in thermal time, the effect of increased daily temperature is to speed up phenology and reduce the length of the crop cycle. Therefore, less biomass can be assimilated and total biomass is reduced, which directly leads to a reduction in yield. This is the main effect driving the decrease in yield as a function of temperature increase seen in Fig. 5. The yield decrease is directly an effect of reduced biomass; the simulated harvest index (ratio of grain mass to total biomass) does not decrease in the simulations (not shown). Fig. 6 also shows that for regions where the temperature effect dominates, the sensitivity of yield to temperature increase depends to some extent on the mean baseline temperature: yields in regions where temperatures are lower are less impacted by higher temperatures. In those regions, the positive impact of higher temperatures on photosynthesis, and thus on yield, tends to compensate the detrimental effect of higher temperature on crop cycle duration.

In Arid regions, on the other hand, the temperature effect is overridden by the effect of precipitation changes. This reflects the fact that plants are mostly water-limited in those areas. This effect is twofold. In the Arid zone as defined in the Köppen classification, crops do not grow everywhere in the model, as some pixels are too dry for vegetation to grow. On average across all models (over 1961–2000), 56% of the Arid zone has no vegetation in the model. Consequently, because we average the simulation outputs over the whole Arid Köppen zone, yield changes reported in Fig. 3 reflect the combination of both the increase (decrease) in yield over “Arid” pixels where crops can grow in the model, and the extension (reduction) of the area of the “Arid” zone where crops can grow (Fig. 7). For instance, for the BCCR model, yields increase by 31% over pixels where crops actually grow within the Arid zone (Fig. 7c); this fraction of the Arid zone, itself, increases by 6% (Fig. 7b); because those new yield values are replacing previously nil values, the averaged yield change over the whole zone – which integrates both effects – increases by a larger 48% (Fig. 7a).

3.4. Effect of CO_2

Fig. 8 compares the projected long-term yield changes in simulations with increasing atmospheric CO_2 concentrations (presented in the previous section) and the yield changes in simulations where CO_2 concentrations are kept constant throughout the 21st century at the year 2000 value. The comparison is done for the A2 scenario, for which the increase in CO_2 is greater, in order to maximize the possible impact of CO_2. Fig. 8 shows that, even under the A2 scenario, the increase in CO_2 has little effect on the projected yield changes. Across all models, yield increases from CO_2 increase are: 1.6%, 1.5%, 6.8%, 2.1% for the “Equatorial fully humid”, “Equatorial with dry season”, “Arid”, and “Temperate” zones.

The impact of increasing atmospheric CO_2 concentrations on simulated yield changes thus remains small, the largest effect

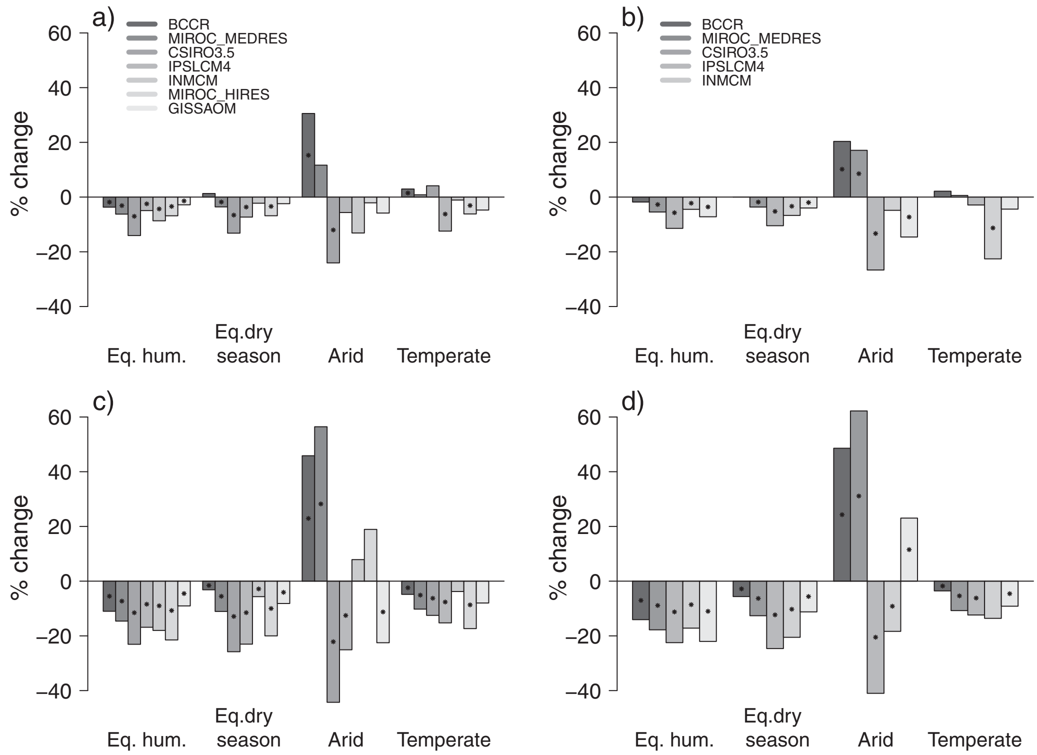

Fig. 3. Average change, in %, between mean simulated yields over 2020–2049 and over 1970–1999, for the different Köppen zones and climate models, for the A1B scenario (a) and the A2 scenario (b). (c) and (d) same as (a) and (b), but for the difference between 2070–2099 and 1970–1999. Dots indicate significant mean yield changes (at a 5% level).

taking place in "Arid" areas. The consistency of this simulated effect with experimental data and other modeling studies will be discussed in Section 4.

3.5. Annual productivity changes

In Section 3.2 we analyzed the impact of climate change on yield by considering the mean annual yield – that is, if multiple crop cycles occur during the year (i.e., in areas where precipitation is no limiting factor, such as Equatorial fully humid areas), we considered the mean yield over the different cycles. However, in those regions, when multiple (e.g., 2) crop cycles take place during the year, it is also possible to consider the sum of the yields from the different cycles – that is, the annual productivity (as opposed to the productivity per cycle). Fig. 9 shows that in this case, yield decrease are actually nearly nil, on average, over these regions. Because on average crop cycles become shorter with higher temperatures, if water availability is not a limiting factor, the number of crop cycles tends to increase, on average, over the area (Fig. 9b). As a result, the total annual yield does not change:

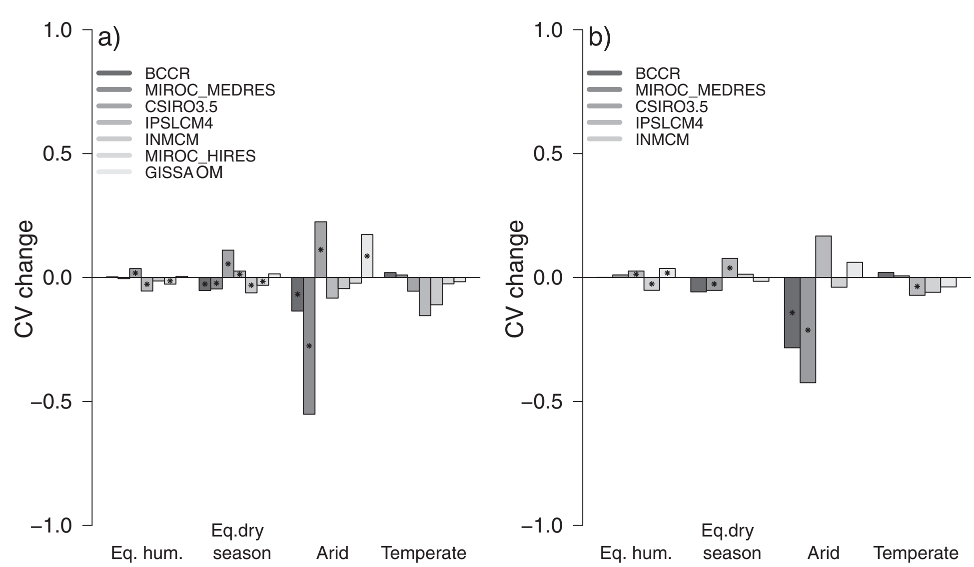

Fig. 4. Average change in simulated yield variability (as expressed by change in the coefficient of variation) between 1970–1999 and 2070–2099, for the different Köppen zones and climate models, for the A1B scenario (a) and the A2 scenario (b). Dots indicate significant variability changes (at a 5% level).

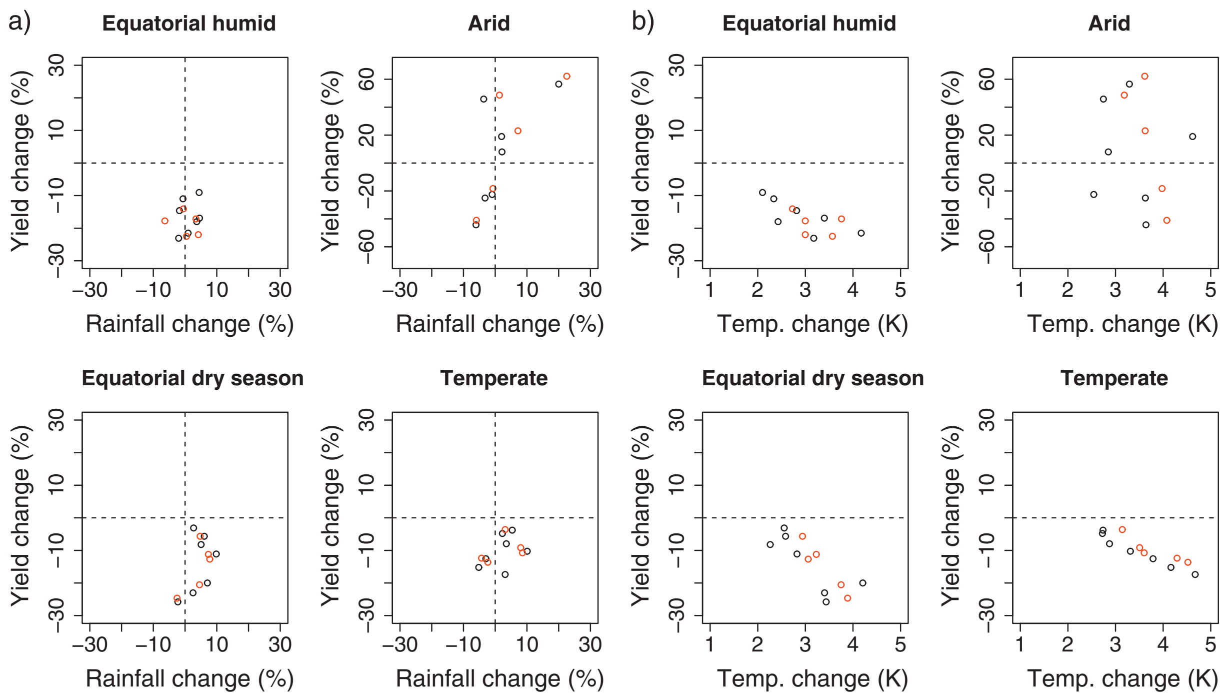

Fig. 5. Simulated yield mean changes (between 2070–2099 and 1970–1999) as a function of projected rainfall changes (a) and temperature changes (b). The different panels correspond to different Köppen zones, the dots to the different climate models. Black dots are for the A1B scenario (7 models), red dots for the A2 scenario (5 models). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

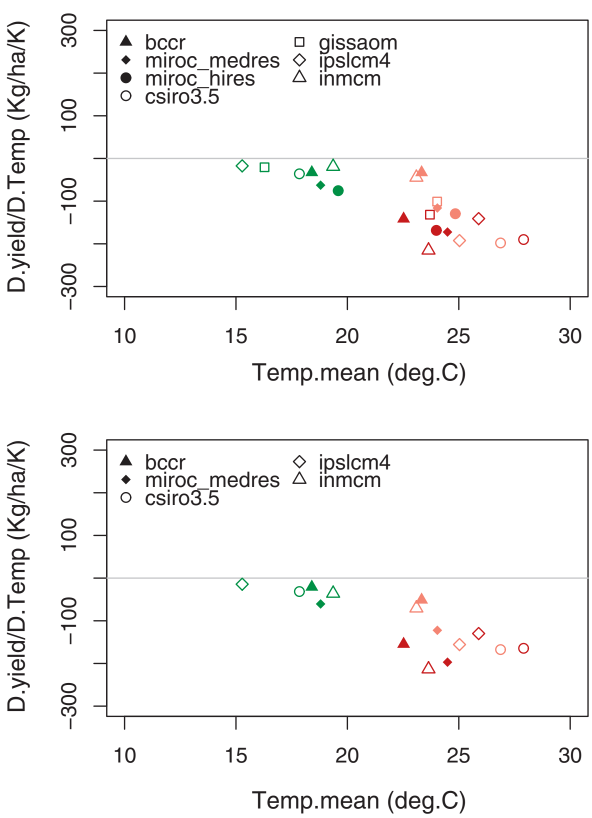

Fig. 6. For both Equatorial zones and for the Temperate zone, under the A1B (top) and A2 (bottom) scenario, ratio of yield change to temperature change as a function of the mean present temperature (1971–2000) for the different zones and climate models (colors correspond to the legend in Fig. 1; green, temperate; salmon, equatorial with dry season; dark-red, equatorial fully humid). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

smaller yields per cycle are offset by an increase in the number of cycles.

4. Discussion

4.1. Projected climate change and yield changes

The main effect of climate change on crop yields in our simulations consists of higher temperature leading to an acceleration of the phenological cycle, thus reducing yields. This effect is compensated in regions with lower baseline temperatures by the positive impact of higher temperatures on photosynthesis. The net effect generally leads, depending on the baseline temperature and the degree of warming in a given climate projection, to yield decreases on the order of −10 to −20% by the end of the century, taking place over most of the study domain: observed Equatorial and Temperate zones account for 69% of the study domain here (excluding sea and desert). Where water availability is the dominant constraint on crop growth, however, large projected yield changes follow precipitation projections. In those regions these changes then tend to be associated with variability changes that act as additional benefit (higher yields and reduced variability) or additional adverse impact (reduced yield with higher variability).

One can note that the scale of impacts is not proportionate to the time horizon considered: although the 2020–2049 time period is intermediate between 1970–1999 and 2070–2099, long-term impacts are generally more than twice those on the shorter term (Fig. 3). This stems from the non-linear evolution of the climatic drivers, in particular temperature, in the context of climate change. Indeed, for Temperate and Equatorial regions in Fig. 5, additional points obtained from intermediate time horizons fall on the same line as results obtained from the 2070 to 2099 period (not shown), underlining the relationship between this climatic forcing and yield change over time. In addition, in some particular cases short-term and long-term projections may not be consistent: for instance, the INMCM model projects, under the A2 scenario, a decrease in

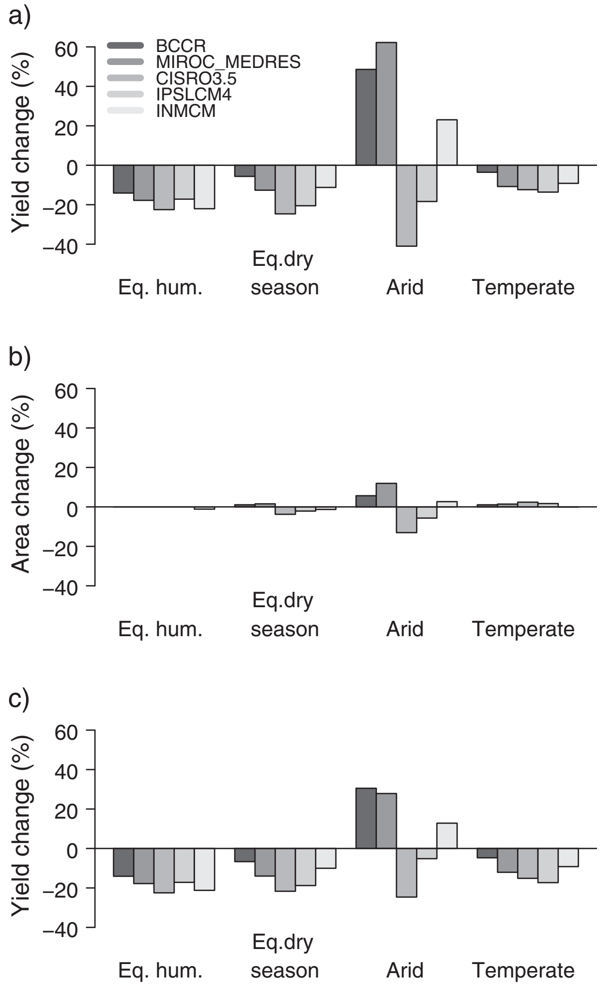

Fig. 7. (a) Average simulated yield change, in %, between 2070–2099 and 1970–1999 over the different Köppen zones and climate models (same as Fig. 3d); (b) projected change in the relative fraction of the corresponding Köppen zone over which crops grow in the model; (c) average simulated yield change, in %, over the different Köppen zones and climate models, when only considering the fraction of Köppen zones over which crop growth actually occurs. All three panels are for the A2 scenario.

precipitation over Arid zones by 2020–2049 (no shown), but a significant increase by 2070–2099 (Fig. 2b). As a result, projected yield changes are negative on the short term, but positive on the long term (Fig. 3b and d). These results underline the interest of considering several time horizons when assessing climate change impacts. Although shorter-term impact assessments undoubtedly provide useful information for immediate agricultural planning and adaptation, they also, by design, only provide a partial picture of the full climate change impacts. Therefore, given the propensity of the lay public to assume proportionality and the difficulty of grasping non-linearities in the context of climate change (e.g., Sterman and Sweeney, 2007), caution should be used when communicating this type of near-term result.

Because warming by the end of the century is greater in the A2 scenario, impacts over both Equatorial zones and the Temperate zone are on average greater in the A2 scenario than in the A1B scenario. Conversely, impacts are less detrimental over Arid areas under the A2 scenario: this somewhat counter-intuitive result stems from the effect of higher atmospheric CO_2 levels on water use efficiency being greater in the A2 scenario, whereas there are little differences in precipitation changes between both scenarios.

The consistency of yield change projections across models reflects the consistency of climate projections: temperature increase being consistently projected by all models, projected yield changes in regions where the effect of temperature change dominates are broadly consistent across models; changes in precipitation, on the other hand, remain largely inconsistent, so that large projected yield changes in regions where the effect of precipitation change dominates diverge across models. Despite the smaller proportion of the Arid Köppen zone (32%), this uncertainty propagates to the aggregated estimated impact over the whole domain. These results underline, fundamentally, the need to narrow the uncertainty in precipitation projections from climate models over Arid areas in order to be able to provide reliable agricultural impact assessments in the Tropics. Here, some models generally predict an increase of precipitation (e.g., MIROC-MEDRES), while others predict drying (e.g., CSIRO3.5). The choice of climate models in this study was based on practical considerations: other models may arguably provide more realistic projections. However, it has to be noted that trying to define a few 'best' models based on evaluation of the models' behavior over current climate does not ensure robust climate projections (e.g., Cook and Vizy, 2006). Using a suite of climate models to quantify the uncertainty thus remains the only possible strategy. It also has to be noted that the expansion of croplands, which in these regions will likely be a component of any strategy towards future food security, has the potential, through modification of land/atmosphere interactions, to substantially alter regional climate (e.g., Davin et al., 2007). This land-use induced climate change is not accounted for in the climate projections used in this study, thus adding to the overall uncertainty in climate projections and subsequent yield changes.

4.2. *Comparison with previous studies*

4.2.1. *Climate effect*

Because we analyze crop yields change from our simulations on a bioclimatic basis, it is difficult to precisely compare our results to other similar large-scale (continental) impact assessments whose results are reported on a geographical basis (Jones and Thornton, 2003; Liu et al., 2008; Nelson et al., 2009; Müller et al., 2009; Schlenker and Lobell, 2010). In addition, impact studies also often differ by climate scenarios, time scopes, crops, methodologies, etc., thus hampering any exact comparison of the different results (Roudier et al., 2011). Here for instance, some large-scale studies use a different metric to assess the impacts of climate change (Nelson et al., 2009), or consider a shorter time horizon (Liu et al., 2008), or consider a mix of C3/C4 crops (Müller et al., 2009).

However, accounting for the uncertainty in precipitation projections in our simulations, the order of magnitude of our results is broadly consistent with previous findings from Jones and Thornton (2003) and Schlenker and Lobell (2010). Based on extensive simulations with the CERES-maize crop model driven by climate projections from the HadCM2 climate model, Jones and Thornton (2003) project an overall decrease of maize yield of −10% over Latin America and Africa by 2050, with impacts varying between −30 and +2% over Sub-Saharan African countries (−14% on average). Although they do not specify which climate effects drive these changes, the spatial homogeneity of their results suggest that they mainly result from the temperature increase. Moreover, using the same model in a later study with a more regional scope (East Africa), Thornton et al. (2009) underline the primary role of temperature increase as the driver of maize yield change, with aggregated yield decreases over the region between −1% and −15% across emissions scenarios and climate models. They also report on the benefits to crops of higher temperatures in specific regions with lower baseline temperatures (below 20 °C). Schlenker and Lobell (2010), on the other hand, use empirical large-scale relationships between climate and yields, extrapolated with projections from 16 climate models, to project crop yield changes in Sub-Saharan

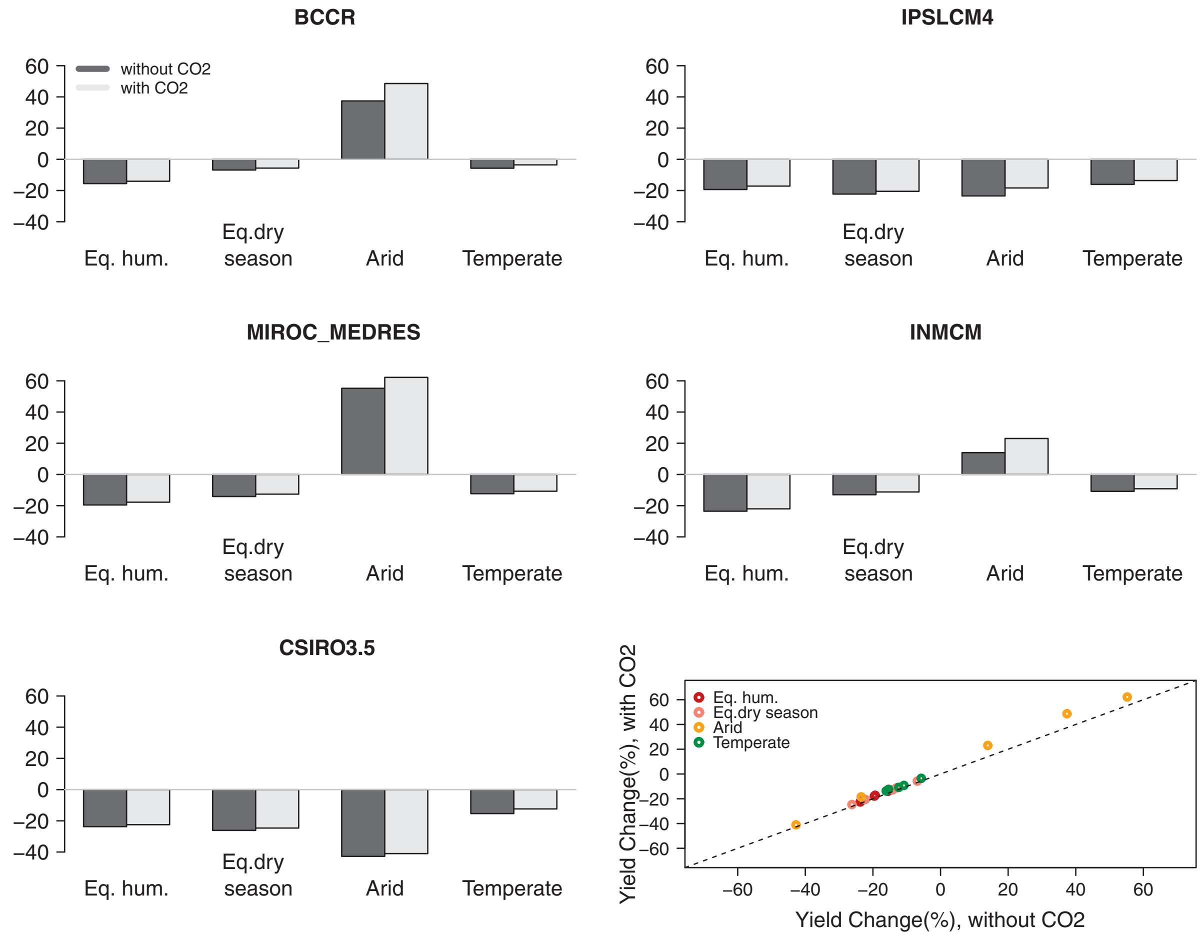

Fig. 8. For the different models, projected yield change between 2070–2099 and 1970–1999 over the different Köppen zones with and without CO_2, for the A2 scenario. The bottom right panel shows the data from all the other panels on a XY plot.

Africa by 2050. They report a projected yield decrease on the order of −20% for C4 cereals, which in their study is entirely driven by the increase in temperature (although the statistical nature of their analysis does not allow them to specify the physiological pathway by which this effect occurs). The previous studies are thus consistent with our result that the main impact of climate change is a temperature-driven yield decrease of −10 to −20%.

On the other hand, in their study with the GEPIC crop model (a GIS-based version of the EPIC crop model) over Sub-Saharan Africa, Liu et al. (2008) project yield increases for millet between +7 and +27% by 2030 (across different emissions scenarios, with projections from the HadCM3 climate model). They attribute those higher yields to higher average temperatures being closer to the optimal temperature for millet. Although the EPIC model also calculates cycle duration in thermal time, they do not report any effect of temperature on phenology. The simulated positive impact in their study, however, may also be related to the way they account for the effect of CO_2 (see below).

4.2.2. The “CO_2 effect”

A major source of uncertainty in crop yield projections is the impact of higher atmospheric CO_2 levels on crop yields (Soussana et al., 2010; Roudier et al., 2011). The magnitude of the impact of higher atmospheric [CO_2] on plant physiology and growth (the “CO_2 effect”) remains a matter of active debate and research (Long et al., 2006; Tubiello et al., 2007; Ziska and Bunce, 2007; Ainsworth et al., 2008). However, the emerging consensus, based in particular on the results of the free-air concentration enrichment (FACE) experiments, is that while the CO_2 effect might be important for C3 plants, increased atmospheric CO_2 levels can be expected to have little to no direct fertilization effect on C4 plants; however they can moderately improve plant resistance to water stress through increased water use efficiency, as a result of lower stomatal conductance and greater intercellular [CO_2] (Long et al., 2006; Leakey, 2009).

The limited effect reported in our simulations in Section 3.4 is consistent with this expectation: increased atmospheric CO_2 levels provide little direct stimulation of C4 photosynthesis (i.e., the fertilization effect), but drought stress is ameliorated as atmospheric [CO_2] increases, so that the strongest effect takes place in Arid zones (see Section 3.4).

In their study with the agro-DGVM LPJmL (Bondeau et al., 2007), Müller et al. (2009) do not separate results for C3 and C4 crops, so that their results cannot be compared to ours here. However, consistent with the above there is in theory little to no direct CO_2 fertilization on C4 crops in the LPJmL model, with the resistance to drought stress being ameliorated (Müller, pers. comm.). Because there is, on the other hand, a strong positive impact of increased atmospheric [CO_2] on the yield of C3 crops, the aggregated yield change (C3 and C4 crops) by 2050 over the Tropics changes from negative to positive in their simulations (e.g., from −7% and −16% to +7.5% and +19.8% over Sub-Saharan Africa and South Asia).

On the other hand, the magnitude of the simulated “CO_2 effect” on C4 crops may partly explain the discrepancy between our results and those of Liu et al. (2008) (see above). Although they do not provide actual figures for simulations with no change in atmospheric [CO_2], they qualitatively report that while maize yields (C4 crop) increase by 3–4% by 2030 over Sub-Saharan Africa when the change

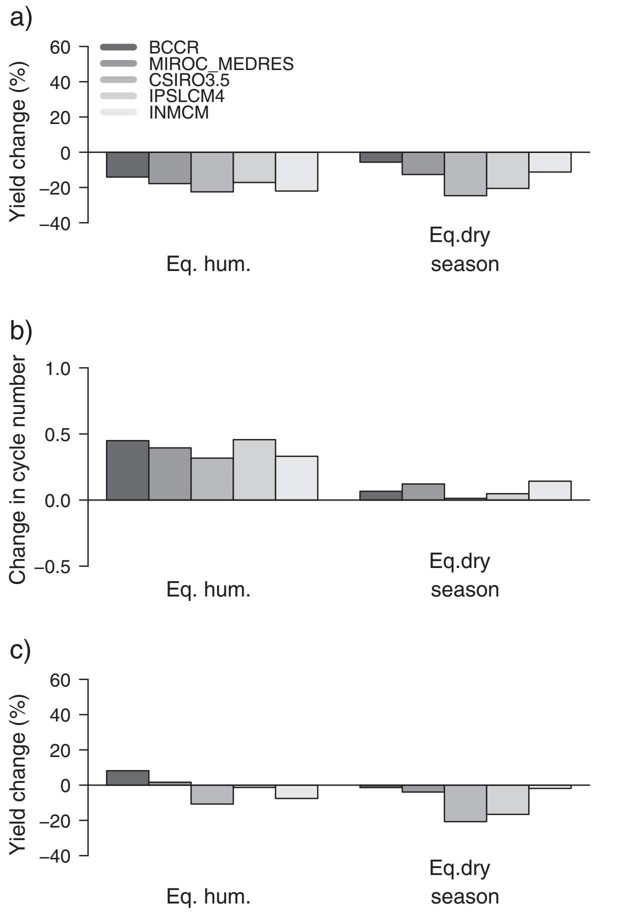

Fig. 9. For both Equatorial zones, in the different climate models, under the A2 scenario: (a) relative change in simulated yield between 2070–2099 and 1970–1999 (same as in Fig. 3d) – i.e., change in productivity per cycle; (b) change in the average number of crop cycles per year (over the whole corresponding Köppen zone); (c) integrated yield change accounting for the change in number of crop cycles (i.e., change in annual productivity).

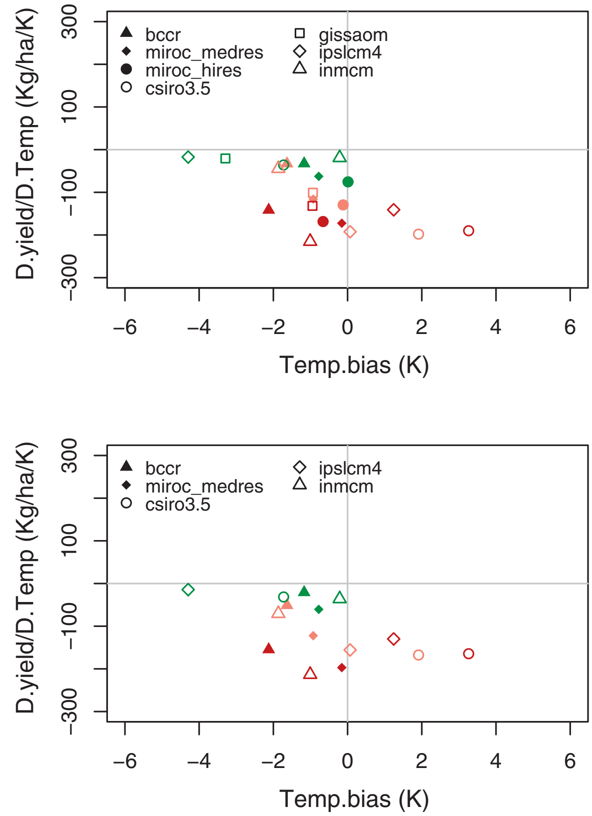

Fig. 10. For both Equatorial zones and for the Temperate zone, under the A1B (top) and A2 (bottom) scenario, ratio of yield change to temperature change as a function of the mean baseline (1971–2000) temperature bias for the different zones and climate models when compared to CRU data (Mitchell et al., 2004) – colors correspond to the legend in Fig. 1; green, temperate; salmon, equatorial with dry season, dark-red, equatorial fully humid. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

in CO_2 concentration is accounted for, they decrease "when not considering the change of atmospheric CO_2" (Liu et al., 2008, p. 229). This suggests that the CO_2 effect is at least partly responsible for the simulated increase of maize yield in their study – and, since it shares the same photosynthesis pathway, for that of millet yield as well (see above). As in many crop models, the EPIC model (on which the GEPIC model in Liu et al. (2008) is essentially based) accounts for the effect of increasing CO_2 concentrations by multiplying daily biomass assimilation by calibrated coefficients. We note that both Long et al. (2006) and Tubiello et al. (2007) indicate that the CO_2 parametrization used in the EPIC model (from Stockle et al., 1992) results in overestimated gains in crop yield at higher atmospheric CO_2 concentrations (both for C3 and C4 crops) when compared to FACE data.

4.3. Limitations of the bioclimatic approach

Although the bioclimatic analysis we adopt offers a number of advantages (Section 2.3.2), it also presents some limitations.

First, an analysis by bioclimatic zones loses the geographical aspect of climate projections and subsequent agricultural impacts. By design, it cannot directly provide results for specific subdomains. As a result, it may miss consistent signals, in terms of climate and yield change, at the regional scale. For instance, our analysis underlines the inconsistency of rainfall projections over our large-scale, tropical study domain as a whole, in particular over Arid regions (Section 3.1); however, Christensen et al. (2007) show that over a more specific regional domain like East Africa, climate models simulations actually provide a more consistent picture–in this case an increase in precipitation. Because pixels from that region are mixed with those from other regions in different bioclimatic zones, our analysis does not allow us to isolate such a regional response. The bioclimatic approach is best suited to provide aggregated results on a larger – e.g., continental – scale.

Second, although it provides a framework to directly use raw climate model simulations as forcing data, the analysis by bioclimatic zones, by itself, does not completely remove climate biases. In particular, for bioclimatic zones that are firstly defined by simple temperature thresholds, climate biases may persist within the different zones. This is all the more the case here as we used simplified Köppen zones, with wider definitions. For instance, the first criterion in the Köppen definition of Equatorial zones is that the minimum monthly average temperature exceeds 18 °C. Hence any warm bias in a given climate model over those regions would propagate to the Köppen Equatorial zones defined within that model. Such biases may then impact the simulated response of crop yields to climate change, since temperature is often the main driver of this response (Section 4.1). Here, for most models and most zones, temperature biases over 1961–2000 remain lower than 2 K in absolute value – mostly negative (Fig. 10) – when compared to CRU data (Mitchell et al., 2004). The IPSLCM4 and GISSAOM models exhibit the strongest biases towards cold temperatures, in the Temperate zone, because of the near absence of temperate pixels on the African continent in those models when compared to observations (Fig. 1). There is thus a comparatively stronger weight of the much colder zones of North India within this bioclimatic zone. On the other hand, CSIRO3.5 suffers from a strong warm bias in Equatorial regions. Because of the dependence on mean temperatures of the relationship between warming and yield change (Section 3.3), the two previous points results in an apparent decreasing trend between temperature bias and sensitivity of yield change to temperature increase (Fig. 10). Because the mean temperature bias, across all zones and climate models, is negative, Fig. 10 also means that our estimates of climate change impacts on crop yield may be overall slightly conservative for those areas. Only for the CISRO3.5 model is it clear that because of the strong warm bias in Equatorial regions, impacts are overestimated in those regions (CSIRO3.5 indeed exhibits the strongest yield decrease in Equatorial regions – Fig. 3).

4.4. Uncertainties in crop model projections and potential for mitigation of climate change impacts

We stress that the results presented in this study should not be viewed as realistic predictions of the actual yield changes that will occur by the end of the century. ORCHIDEE-mil, as the crop model SARRAH from which it is derived, only simulates the yield of a modern cultivar, as grown on an experimental station: sown at high density and optimally managed (in terms of fertilization, but also diseases and pests). Simulated yields correspond to the climatic attainable yield. Our results thus underline the scope of potential climate-related impacts of climate change on crop yields. In addition, we aggregated simulation outputs over the whole study domain, not using a realistic cropland distribution for the present or areas projections for the future: our results are thus relevant to the potential crop productivity over the study domain, not the actual productivity over current and future croplands. We only simulated a single C4 millet cultivar, with a fixed (thermal) cycle duration; however, a large diversity of cultivars is grown in reality, with potentially different responses to climate change. In particular, farmers in Africa often rely on traditional hardy cultivars with a photoperiodic cycle, i.e., crops whose cycle duration depends on the seasonal evolution of day length and not on temperature sums (e.g., Kouressy et al., 2008). Such cultivars will then be less sensitive to the increase in temperatures that in our results acts as the main driver of crop yield change. It thus remains unclear, overall, how the projected potential impact of climate change will translate into changes in actual, on-farm crop productivity changes. It has to be noted that because of poor soil fertility and low input levels, combined with extensive agricultural practices (e.g., low sowing densities – Bationo et al., 1992), actual yields in Africa and, to a lesser extent, in India, fall short of the potential yields by a large measure. Numerous studies have shown that the main limitation to current crop yields in those regions is the lack of organic and mineral fertilization: for instance, Bationo et al. (1993,2007) show that in West Africa, on-farm yields of millet or sorghum can be multiplied up to tenfold (typically from 200 kg/ha to 2 t/ha) and sustained at this level through the use of organic amendments (e.g., restitution of crop residue) and mineral fertilizers (in particular phosphate) combined with higher sowing densities. In India, Murty et al. (2007) report differences of a factor 2–4 between on-farm millet and sorghum yields and potential yields obtained on experimental station plots. Therefore, even considering the potential adverse climate change impacts presented in this study, there is a very large and untapped potential of yield increase through the use of improved agricultural practices: it is obvious that filling the current “yield gap” in those regions would more than offset the negative impact of climate change.

In addition, adaptation of agricultural practices can at least partly mitigate the impact of climate change on crops. For example, in arid regions, development of irrigation, soil water conservation and water harvesting techniques (Howden et al., 2007) can help mitigate adverse changes in water availability. Similarly, changes in crops, in cultivars or in cropping systems can mitigate the impact of higher temperatures on phenology. Some of our results point to the potential for such mitigation: in Section 3.5, we showed that in regions where water availability is not a limiting factor, total annual productivity was not impacted by climate change, because smaller yields per cycle were offset by an increase in the average number of crop cycles (Fig. 9). As they do not integrate considerations on soil fertility, crop rotations or even farmers' work load, we do not claim that these results represent a realistic future response of farmers to climate change; however, they suggest that in some cases it may be possible to adapt cropping systems in order to keep up with potential productivity and mitigate the impacts of climate change.

In summary, it is possible to suggest that in developing countries of tropical regions, implementing more intensive agricultural practices and adapting agriculture to climate and environmental change has the potential to more than offset the projected impacts of climate change. It is outside the scope of this paper to discuss if such improvements will allow meeting the increase in demand, as projected by Collomb (1999). However, one can note that such structural changes require investments, institution and human capital building that will not occur without active development and agricultural policies: for example, increasing investment in irrigation infrastructure; ensuring availability and affordability of agricultural inputs (seeds, fertilizers); ensuring appropriate transport, storage and markets for both inputs and products; etc. (Howden et al., 2007). In Africa in particular, the last decades have overall seen little progress on those fronts: per capita cereals production declined by 13% between 1965 and 2000 (FAO, 2001), with the increase in population outpacing the increase in food production. Most of the increase in production, moreover, has been achieved through the expansion of croplands, not through increased yields, a strategy which is not sustainable over the long term (Bationo et al., 2007). Given that the necessary changes in the agricultural system did not take place in the past decades, they certainly cannot be taken for granted in the future; in which case, the impact of climate change will be a significant additional strain on the food system and will further challenge future food security.

Besides uncertainties on the drivers of future yield change (climate change, CO_2 effect, land management), uncertainty in our results also stems from the necessarily imperfect large-scale modeling of crop yields: in such a framework many processes are implemented in a simple, aggregate form, or are sometimes missing. For instance, the effect of certain climatic extremes are not taken into account, such as the impact of intense heat during particular development stages on grain quantity and quality (Wheeler et al., 2000), or the impacts of floods from heavy rainfall events. Moreover, in climate-driven crop models such as ORCHIDEE-mil, potential impacts from the interactions of climate and atmospheric CO_2 changes with biotic factors (pest, deseases or weeds), are also not accounted for (Soussana et al., 2010). It is not clear, however, whether all the relevant effects and their interactions can be implemented in a single, exhaustive crop model. It can be argued that the best approach to provide a complete assessment of the impact of climate change on crops is through the use of a “hierarchy of models” of different scale and complexity (Soussana et al., 2010). In this context, ORCHIDEE-mil, and agro-DGVMs in general, provide a tool to carry out mechanistic, large-scale and spatially explicit assessments in a straightforward manner, allowing in particular to span the uncertainty in climate model projections. In addition, the bioclimatic approach used in this study offers a framework to analyze simulations directly forced by climate models outputs, thus preserving the internal consistency of these climate projections. By analyzing impacts in different bioclimatic zones with different climatic constraints and plant responses, this approach also allows one to clearly highlight the main climatic drivers of the impact of climate change on crops.

5. Conclusion

Using a newly developed agro-DGVM driven by projections from several climate models and scenarios over Africa and India, we find that the potential productivity of one of the most important staple crop in those regions, millet, will overall decrease, on average over all models and scenarios, by −6% (individual model results ranging from −29% to +11%). Analyzing yields on a bioclimatic basis through the Köppen classification allows us to underline the main climatic drivers behind those changes: we find the main impact to be a moderate, but consistent across climate projections, temperature-driven yield decrease over Equatorial and Temperate Köppen zones. In Arid zones, on the other hand, larger yield changes occur that are driven by precipitation changes, but with much more uncertainty: this directly reflects the uncertainty in precipitation projections from climate models. The uncertainty in aggregated impacts reflects the uncertainty over water-limited areas, underlining the need to narrow the uncertainty in precipitation projections over dry areas, if reliable agricultural impact assessments over tropical regions are to be provided. Our results also are consistent with the expected limited magnitude of the impact of CO_2 on crop yields for C4 crops. While such climatic impacts further increase the challenge of achieving future food security in developing countries in the Tropics, most of these impacts can arguably be mitigated through adaptation measures and improved agricultural practices.

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