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Crop yield reduction in the tropics under climate change: processes and uncertainties

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Abstract.

Many modelling studies examine the impacts of climate change on crop yield, but few explore either the underlying bio–physical processes, or the uncertainty inherent in the parameterisation of crop growth and development. We used a perturbed–parameter crop modelling method together with a regional climate model (PRECIS) driven by the 2071–2100 SRES A2 emissions scenario in order to examine processes and uncertainties in yield simulation. Crop simulations used the groundnut (i.e. peanut; *Arachis hypogaea* L.) version of the General Large–Area Model for annual crops (GLAM). Two sets of GLAM simulations were carried out: control simulations and fixed–duration simulations, where the impact of mean temperature on crop development rate was removed. Model results were compared to sensitivity tests using two other crop models of differing levels of complexity: CROPGRO, and the groundnut model of Hammer et al. (1995).

GLAM simulations were particularly sensitive to two processes. First, elevated vapour pressure deficit (VPD) consistently reduced yield. The same result was seen in some simulations using both other crop models. Second, GLAM crop duration was longer, and yield greater, when the optimal temperature for the rate of development was exceeded. Yield increases were also seen in one other crop model. Overall, the models differed in their response to super–optimal temperatures, and that difference increased with mean temperature; percentage changes in yield between current and future climates were as diverse as -50% and over +30% for the same input data. The first process has been observed in many crop experiments, whilst the second has not. Thus, we conclude that there is a need for: (i) more process–based modelling studies of the impact of VPD on assimilation, and (ii) more experimental studies at super–optimal temperatures.

Using the GLAM results, central values and uncertainty ranges were projected for mean 2071–2100 crop yields in India. In the fixed–duration simulations, ensemble mean yields mostly rose by 10 to 30%. The full ensemble range was greater than this mean change (20–60% over most of India). In the control simulations, yield stimulation by elevated CO2 was more than offset by other processes — principally accelerated crop development rates at elevated, but sub–optimal, mean temperatures. Hence the quantification of uncertainty can facilitate relatively robust indications of the likely sign of crop yield changes in future climates.

Keywords: Crop model, climate change, quantifying uncertainty, development rate, transpiration efficiency, vapour pressure deficit

1. Introduction

Climate change has direct and indirect impacts on crop growth and development. Higher atmospheric concentrations of CO_2 have a direct impact on C3 crops by increasing photosynthesis and the efficiency of water use. This effect is potentially significant, although only relatively recently (1999 onwards; see Luo and Lin, 1999) has parameterisation of this effect become common in crop model assessments of climate change. Indirect effects result from changes in weather and climate that result from higher levels of greenhouse gases, for example changes in the mean and variability of temperature or rainfall. Mean temperatures affects crop duration (e.g. Challinor et al., 2005c), whilst temperature extremes during flowering can reduce the grain or seed number (Wheeler et al., 2000). Changes in temperature will also affect the potential evapotranspiration, with actual evapotranspiration determined by any concurrent changes in water availability and radiation.

Both the direct (Long et al., 2006) and the indirect (Mearns et al., 1999) effect of climate change on crops are significant sources of uncertainty in impacts assessments. This study builds on previous work which used a range of crop and/or climate model parameters to quantify the uncertainty in the response of crops to mean temperature (Challinor et al., 2005a, 2007a) and elevated CO_2 (Challinor and Wheeler, 2007). The principal crop model used is the General Large–Area Model for annual crops (GLAM; Challinor et al., 2004). In order to focus more clearly on the response of the crop to climate change, only a single climate change scenario is considered (a regional climate model scenario for 2071–2100). This choice is further justified by examining only mean yields (i.e. averages over the period 2071–2100), since for mean yield the relative contribution of crop simulation uncertainty to that of uncertainty in climate is large. The same is not true of yield variability, where climate uncertainty dominates (Challinor et al., 2005a).

A simple, though not necessarily intelligent, adaptation is also considered: by fixing the timing of the development stages of the crop under climate change so that it equals that of the baseline (i.e. current) climate, the impact of mean temperature on duration is removed.

Any impacts of climate change seen in these simulations is due to other processes such as the direct CO_2 effect and changes in the hydrological cycle. Hence this method allows the impact of individual crop processes, and their uncertainties, to be assessed. A similar method was used by Challinor et al. (2007a) to examine the relative importance of changes in the mean and extreme of temperatures. For this reason, the impact of temperature extremes on flowering is not simulated in the current study. Limiting the processes studied in this way isolates them and permits an assessment of their relative importance.

The study has three aims. The first is to identify the (indirect) bio–physical processes that are important in determining yield under climate change, and quantify their impacts. These processes may vary geographically with climate, although the methods themselves are not location–specific. The second aim is to identify the key uncertainties that emerge: which parameters contribute most to the total uncertainty in the climate change projection? Since the parameters in GLAM map directly onto specific processes in a transparent way, these results are relevant beyond the GLAM framework: they can be used to assess the importance of these processes, and their associated uncertainties, in other crop models and also in field studies. The generality of the results from the first and second aims is discussed in section 4.

The third aim is more specific than the other two: to put geographically–specific central values and uncertainty ranges on the changes in groundnut yield under the 2071–2100 Special Report on Emissions Scenarios (SRES) A2 scenario. This is carried out for both the adapted and non–adapted crops. In reality, of course, the adaptive measures used by the end of the century may be something that cannot currently be envisaged. This is an important caveat to the third aim of this study. It is also a motivation for the first two aims, since these seek to analyse fundamental processes towards which adaptation should be geared.

The study region is India, where extensive evaluation of GLAM has been carried out (Challinor et al., 2006, 2007a, 2005b, 2005d, 2004). The key bio–physical processes identified may vary with crop species. However, many annual crops, particularly those that share the C3 photosynthesis pathway, are likely to show similar broad responses to the crop studied here (groundnut, also known as peanut; *Arachis hypogaea* L.). A third factor may affect the generality of the results: the choice of crop model. To address this, simulations with two further crop models (CROPGRO: Boote and Jones, 1998; and the groundnut model of Hammer et al., 1995) were carried out, in order to assess the sensitivity of those models to the identified processes.

2. Methods

2.1. Large–area crop modelling

The impact of climate variability and change on food production has been assessed using a number of methods. Empirical parameterisations of crop yield have been combined with climate modelling and economic modelling (e.g. Iglesias et al., 2000), with the advantage of quantifying impacts in human terms such as levels of risk to hunger (Parry et al., 2004). A disadvantage of this method is that it may introduce errors through the linearisation of crop yield equations (Challinor et al., 2006) and/or the use of monthly data, which does not account for sub–seasonal weather variability (Challinor et al., 2007b, 2005c). Detailed process–based crop models have also been used with climate model output (e.g. Carbone et al., 2003), sometimes scaled down in space (e.g. Busuioc et al., 2001). This method can capture the complex bio–physical processes associated with climate change that are usually overlooked by empirical studies. However, these models produce results which are location–specific, since the yields depend upon the specific crop variety, soils and management practices used. Whilst this problem can be overcome through the identification of representative farms, this choice can itself be problematic (Antle, 1996; Luo and Lin, 1999). The problem can also be overcome by applying a bias correction at the output stage (Jagtap and Jones, 2002). Whilst this is a pragmatic approach, some of the benefits of process–based modelling are lost by calibrating outside the model structure: the coherent simulation of the simulated aspects of crop growth and development is clearly not realistic if a large bias correction is applied to yields.

Process-based crop modelling can also be carried out at the scale of the climate model, providing climate is believed to influence crop yield on that scale (Challinor et al., 2003). The result is a model of intermediate complexity: less complex than location–specific models and more complex than empirical parameterisations. GLAM is a large–area crop model of this sort. This model does not represent the heterogeneity within a climate model grid cell and as a result it has a lower input data requirement than point–based models. Since it is also less complex than many point–based models, the risk of over–parameterisation is reduced (Cox et al., 2006; Sinclair and Seligman, 2000). GLAM contains parameterisations of the mechanisms through which a crop responds to weather and climate. It can therefore turn time series of weather into time series of crop yield. Being designed to operate with climate model data in this way is an advantage for a study such as this one. However, this method can omit important fine-scale information on climatic (Baron et al., 2005) and/or non–climatic (Challinor and Wheeler, 2007) sources of yield variability. Furthermore, there is no evidence of any link at the large scale between yield and non–climatic factors such as management practices, pests and diseases. Hence this may not be an appropriate scale for the study of non–climatic influences on yield. Despite these issues, large–area crop modelling has shown promising results in current climates in India (Challinor et al., 2007a, 2006, 2005b, 2005d; Wheeler et al., 2007) and in other tropical regions (Bergamaschi et al., 2007; Chee-Kiat, 2006; Osborne, 2005).

2.2. Input future climate scenario

The input future climate data for this study is taken directly from the PRECIS regional climate model (http://precis.metoffice.com/) simulations of IITM (2004). These simulations did not include sulphate aerosols. The greenhouse gas emissions for the chosen simulation was that of the Special Report on Emissions Scenarios (SRES) A2 storyline for 2071–2100. This is one of the most fossil fuel intensive scenarios, with emissions rising monotonically from present–day values ($<$ 10 Gt of carbon) to over 25 Gt in 2100, leading to an approximate doubling of present–day atmospheric CO_2 by the end of the century (IPCC, 2001). The input weather data for the crop model was solar radiation, rainfall, and daily maximum and minimum temperatures (T_{max} and T_{min}). Vapour pressure deficit (VPD) was calculated using maximum and minimum temperatures (Tanner and Sinclair, 1983), a method which has independently been shown to produce good results (Wang et al., 2004).

The future climate scenario produces a warmer, wetter and more variable monsoon over most of India (figures 1a and 1b). Such an increase in the mean and interannual variability of monsoon rainfall (i.e. intensification of the monsoon) has been found in other studies (Turner et al., 2007; May, 2004). O'Brien et al. (2004) and Sivakumar et al. (2005) briefly review a number of studies of projected changes in the Indian summer monsoon, and they are in general agreement with this result. Those studies also show that the effect of the inclusion of sulphate aerosols, which is more realistic than their omission (see also IPCC, 2001), is to dampen the strength of the monsoon relative to simulations without sulphate aerosols. However, the inclusion of sulphate aerosols does not necessarily lead to a weakening of the monsoon under climate change. The intensification of the monsoon in the simulations used here suggests that water becomes less limiting in the future climate scenario, so that changes in water availability are not the principal driver of changes in crop yield.

The increase in precipitation over most of India results in an increase in atmospheric water content (by mass) of around 10–20%. However, relative humidity (RH) falls over the vast majority of the country. This suggests that for significant periods during the monsoon, precipitation is sufficiently high that it does not have a large impact on VPD, at least on timescales greater than approximately one day (see Monteith, 1986). Most of the decreases in RH are of less than 5%. In contrast, differences in VPD are mostly in the range 15–30%. This change is not sensitive to the method used to calculate VPD: two methods were used, the first based on mean daily temperature and relative humidity, and the second based on T_{max} and T_{min}, as described above (see also Challinor et al., 2004). Whilst these methods produced different absolute values of VPD, similar changes between the baseline (see section 2.3) and scenario values were found in both cases. Furthermore, these changes were of greater magnitude than the differences between the two methods. Hence this is a robust change.

Four regions are studied in particular detail in this paper: north–west (NW), the north–western part of Gujarat (GJ), a region in central India (CE) and part of the southern peninsula (SP) (figure 1a). Mean VPD in CE is mostly between 0.6 and 0.9 Pa, whilst in GJ it is mostly in the range 0.9–1.2. These values are typical of most of India, the exceptions being north of 26°N, where VPD is mostly 1.2–1.5 Pa, and SP and south of SP, where VPD is mostly in the range 1.8–2.4 Pa. In NW VPD is in the range 1.8–2.4 Pa. The largest changes in VPD between the baseline and scenario climates are seen in NW, followed by SP, GJ and finally CE. Associated with the high VPD in NW and SP is low rainfall, which causes plant water stress (see Challinor and Wheeler, 2007).

The increases in VPD are mostly driven by temperature changes, which increase the capacity of the air for holding water vapour. future climate scenario the mean temperature increases across all of India, by between 2 and 6 °C (figures 1c and 1d). Based on seasonal averages, T_{max} increases by more than T_{min}, so that the amplitude of the diurnal cycle increases. Whilst recent observations of T_{min} and T_{max} in many parts of the world do not show the same result (Parker, 2006), there is evidence of this trend in temperatures in India (Arora et al., 2005). Since the VPD used by the crop model is proportional to $T_{max} - T_{min}$, this preference for daytime over nighttime heating contributes to the VPD increase seen by GLAM. The impact of some of the changes described here has also been studied by Challinor et al. (2007a, 2006).

2.3. Crop yield simulations

Crop yield simulations for the climate change scenario were carried out using the General Large–Area Model for annual crops (GLAM; Challinor et al., 2004; Challinor et al., 2006). The model, as well as the simulations of crop yield under the baseline climate (1961–1990) that are used in the current study, are described in more detail in Challinor and Wheeler (2007). That study is referred to hereafter as CW07. Four sets of baseline simulations were produced in that study, and these are described in table I. These four sets of simulations were designed to quantify the uncertainty associated with the parameterisation of crop growth. They varied the parameters that control transpiration and assimilation (i.e. transpiration efficiency). CW07 also produced simulations with the baseline climate but with an elevated CO_2 (CO_2–only simulations), and these are used in the current study to isolate the impact of non–CO_2 effects.

Planting in all simulations referred to in this study occurs on the first day within the planting window on which the available soil moisture exceeds 50% of the maximum. Since water availability increases in general between the two time periods, the planting window was not changed for the scenario simulations. The parameter sets used for the scenario simulations in the current study, as well as the soils and planting window data, are those of CW07. These parameter sets are those that reproduced observed large–scale yields (based on a district–level data set) in the baseline climate and observed changes (based on free air CO_2 enrichment and controlled environment studies) in yield , leaf area index (LAI) and specific leaf area (SLA) under elevated CO_2 with no associated change in climate. A number of parameter sets were rejected by CW07 based on these comparisons. The surviving 18 parameter sets are summarised in table I and listed in Appendix A. Each of these parameter sets is an equally plausible representation of crops growing under the scenario climate. Differences in yields across these parameter sets is therefore a measure of the uncertainty in yield associated with input parameter uncertainty.

The 18 simulations were repeated with one modification made to the model: instead of being determined by thermal time, the duration of each crop development stage was fixed, on a year–by–year basis, at the corresponding duration of that stage in the baseline simulation. For these fixed–duration simulations, then, there was no impact of mean temperature on crop development. Whilst this is a departure from reality, it remains sufficiently realistic for our purposes since it approximates the use of a longer–duration crop. For many regions, then, these simulations represent a form of adaptation, although not necessarily an optimal one. The advantage of this method over a change in genetic coefficients is that it permits the direct comparison with baseline simulations in a manor that factors out completely the impact of mean temperature on development.

GLAM accounts for many processes that are important under climate change. The model contains parameterisations of the impact of changes in atmospheric CO_2 on transpiration efficiency (TE) and SLA, as well as the impacts of mean temperature on crop duration. Subseasonal processes are also parameterised, so that changes in temperature, radiation, atmospheric humidity and water availability will affect evapotranspiration and crop growth and development. Daily values of VPD, for example, will affect TE. Some processes are not accounted for in this study. The impact of increased ozone concentrations or temperature on transpiration efficiency (as a surrogate for assimilation rates) is not considered. The impact of elevated temperature alone would be to increase TE (Bernacchi et al., 2006), whilst the impact of elevated ozone alone would be decrease TE (Long et al., 2005). In reality these effects interact both with each other and with CO_2 concentrations (Bernacchi et al., 2006). Interactions between temperature and elevated CO_2 may (Rötter and van de Geijn, 1999; Easterling and Apps, 2005; Long et al., 2004) or may not (Morison and Lawlor, 1999) be important for crop growth and development (see Tubiello and Ewert, 2002; Porter and Semenov, 2005 for further discussion). Interactions between water stress, nutrients and CO_2 concentrations are not considered, and neither is any potential downregulation or acclimation to elevated CO_2. CW07 has some further discussion on these issues. Finally, the impact of changes in plant pests and diseases, which has been researched less than impacts on yield (Chakraborty et al., 2000), has not been considered in this study.

In summary, 36 sets of GLAM simulations were carried out for this study: 18 sets with the variable–duration crop and 18 sets with the fixed–duration crop. These 36 sets of simulations were compared to the baseline simulations (Control, High Baseline TE, Reduced Physiological Transpiration Limitation, Reduced VPD–TE Interaction; see table I of CW07). Each set of simulations consists of thirty years of crop yield for a number of grid cells. For clarity and conciseness, a set of GLAM simulations is referred to simple as 'a simulation'. Unless otherwise stated this includes all of the 787 grid cells for which GLAM has been calibrated by CW07. All results presented are for averages across the whole thirty year period. All cited percentage changes in yield refer to the thirty–year average from the respective baseline simulation. Since the climate input data was the same in all four baseline simulations, these simulations have the same planting dates (for a given year and location). Similarly, the planting dates across all 36 scenario simulations were the same.

2.4. Sensitivity analysis

Sensitivity analyses were performed with CROPGRO (Boote and Jones, 1998) and with the groundnut model of (Hammer et al., 1995) (hereafter referred to as QNUT) in order to compare the response of these models to elevated temperature and humidity to those of GLAM. CROPGRO is a widely used crop simulation model, and QNUT, whilst not currently used widely, formed the base for the development of the legume model template in APSIM (Wang et al., 2002). Note that CW07 compared the response to elevated CO_2 of these models (using the same parameter sets as those used here) to that of GLAM. QNUT and CROPGRO were not calibrated to reproduce observed yields. Instead, standard parameter values were used where possible in order to ensure that the model was being used within operational limits. The parameter set used for the QNUT model was that of Virginia Bunch, with one modification: the thermal requirement was reduced in order to give the crop a duration of around 140–150 days. The genetic coefficients used for the CROPGRO simulations were those of TMV2 as calibrated for use in India by Kakani (2001). Weather inputs for the two crop models came from the thirty–year time series in each of the grid cells from the regions NW, GJ, CE and SP shown in figure 1a. Each of these regions has between 23 and 25 grid cells. The crop was sown on the same day as in the GLAM simulations. The final yield from all (690 to 750) simulations within each region were averaged in order to produce a value for each region.

The response of the models to elevated temperature and humidity was tested separately. The crop response to elevated CO_2 was turned off for all simulations, in order to facilitate the attribution of yield changes to either temperature or humidity changes. The sensitivity of yield to mean temperature was tested using both irrigated and rainfed simulations. The four chosen regions have different mean temperatures, so that no artificial variation of temperature was required for this sensitivity analysis. This has the advantage of being more realistic and the disadvantage that temperature is not the only variable that changes across location. The sensitivity of yield to changes in atmospheric humidity was tested using rainfed simulations only, since humidity and water supply are correlated. Two methods were used for the CROPGRO simulations: (i) directly changing the vapour pressure deficit (VPD) by multiplying it by 1.5. (ii) indirectly changing VPD by altering the maximum and minimum daily temperatures (by +2 and -2 °C, respectively). In the QNUT simulations, only the first of these methods was used, since radiation use efficiency in this model has a strong dependence on daily maximum and minimum temperatures. In CROPGRO, the indirect changes were carried out using one of two options for calculating evapotranspiration: either the Ritchie version of the Priestly–Taylor equation, or the Penman–FAO method (see Boote and Jones, 1998). The indirect method has the advantage of having consistent temperature and humidity, and the disadvantage that observed changes may not be due to changes in VPD, making comparisons with GLAM more difficult. The direct method is less internally consistent, but has the advantage that any changes in yield are definitely the result of the changes in VPD.

It is possible that results using parameter sets calibrated to reproduce observed yields (as is the case with the GLAM simulations) would produce a different sensitivity to temperature and VPD to that found here. This was not done for this study since scale issues mean that it is not clear how point–based crop models such as CROPGRO and QNUT would be calibrated to reproduce large–area yields (see section 1). In order to minimise the impact of any bias due to the choice of parameter values, all the results presented are normalised by the control simulation yields. For the CROPGRO model, some attempt to examine a range of calibrations was made: two values (High and Low: 0.82 and 0.22) of the soil fertility factor (SLPF) were used for each simulation.

The fact that CROPGRO and QNUT are designed for use with point–based weather data rather than large–area gridded data is a further reason for considering the results of the sensitivity analyses to be preliminary rather than definitive. However, all three models used are process–based, so that despite these limitations, the level of consensus between the CROPGRO, QNUT and GLAM simulations provides an indication of the likely level of importance of the bio–physical processes observed in GLAM. Where consensus exists, there is sound reason to believe the results. Where there is no consensus, future work can be aimed at understanding why not. In either event, a crop modelling study at the field scale using fully–calibrated simulations with these two models, and with full representation of parameter uncertainty, would be a useful way to test further the validity of the results found in this study.

3. Results

3.1. Crop yield ensemble

Differences in the mean planting date between the scenario and baseline simulations were small: less than three days for 90% of the grid cells, less than six days for 99% of the grid cells, and less than nine days for the remaining grid cells. Differences in yield are therefore not, on the whole, due to differences in planting date. The 18 variable–duration simulations were used to assess the differences between the parameter sets used. These differences can be seen in figure 2, which presents scenario yields for the Gujarat (GJ) and central India (CE) regions (see figure 1a). The choice of transpiration efficiency (TE) in both the baseline and scenario simulations is shown to contribute to uncertainty (High Baseline TE and Small/Large TE Increase simulations). However, changes in TE do not always act systematically, and the impact of different parameter sets can vary between the two locations. The relationship between VPD and TE is also important in both locations, as is shown by the Reduced VPD–TE Interaction simulation. However, VPD in these two regions (see section 2.2) was not sufficiently low as to be affected by the switching on/off of TE changes in humid environments (see the [no] TE Increase at Low VPD simulations in figure 2). The response of yield to the higher value of physiologically–limited maximum transpiration is not the same at the two locations. This is because LAI is higher, and increases by more, in GJ than in CE, so that in GJ greater use can be made of the possibility of increased transpiration.

The 18 fixed–duration simulations were used to assess the indirect impact of elevated CO_2 on crop yield. Figure 3 shows the scenario yields as a percentage difference from the baseline yields. Also shown are the simulations of CW07, which used the baseline climate but with an elevated CO_2. Differences between these two simulations are due only to the indirect effects of CO_2 (excluding the impact of mean temperature on duration). These differences indicate that the indirect effect of CO_2 on crop yield is negative. Taking the difference between the scenario and CO_2–only simulations, averaged over all ensemble members, shows reductions in regionally–averaged yield of 16% (CE), 28% (GJ), 49% (SP), and 60% (NW). These reductions in yield are rank in the order of the percentage changes seen in VPD between the baseline and scenario climates (see section 2.2). This, together with a sensitivity analysis performed with GLAM (not presented), shows that the changes in yield in GLAM are attributable primarily to increases in VPD, which acts to reduce TE.

Contrasting the fixed– and variable– duration simulations reveals the impact of mean temperature changes on crop yield, as mediated through changes in crop development. Figure 4 shows this contrast for two regions. In GJ, temperatures become sufficiently high that the optimal temperature for development (T_{opt}) is exceeded, and crop development slows, resulting in an increase in yield. In CE, crop duration, and hence yield, fall because T_{opt} is not commonly exceeded. Figure 5 shows this contrast more globally and in a different way: for most of India, where temperatures remain below T_{opt}, the majority of variable–duration ensemble members show a reduction in crop yield. Hence the uncertainty in the response of the crop to elevated CO_2 is smaller than the magnitude of the impact of mean temperature on duration. The ensemble average yield (i.e. the mean across years and ensemble members) in these simulations falls by 10–40% over most of India, and the standard deviation across ensemble members is 5–10%. In contrast, in the fixed–duration simulations yield increases in all regions except those where water is limiting. However, the magnitude of these increases is far from certain, as can be seen in figure 6: whilst the ensemble mean yields most commonly rise by between 10 and 30%, the standard deviation across ensemble members (10–15%) is a significant fraction of this. The full range from the ensemble is greater than the mean change (20–60% over most of India).

Ensemble mean yield increases of above 30% are seen in some regions. These tend to be associated with regions where increases in temperature (and possibly VPD) cause the potential transpiration to rise.

In summary, the results from the GLAM simulations have identified two processes that are important in determining yield in India under the chosen 2071–2100 scenario: firstly, the impact of decreased humidity on assimilation and secondly the impact of mean temperature on development rates. In GLAM the second of these processes has the largest impact. We now go on to examine both of these processes in two other crop models, as described in section 2.4.

3.2. Sensitivity analysis

Figure 7 show the impact of increased VPD on yields in the two other crop models. QNUT consistently shows a reduction in yield at high VPD. CROPGRO shows a reduction in yield in most, but not all, of the simulations. There is a large spread of results in the CROPGRO simulations using the direct multiplication method (VPD=VPD*1.5). Reductions in yield are only found for GJ and CE, regions which have relatively high water availability and low VPD. Hence these are regions where VPD, rather than water, is likely to be limiting. The average impact across all simulations which show a reduction in crop yield is 13%, and 42% of all simulations lie within a range of ±10% from this value. GLAM, in comparison, shows a greater impact of humidity on yield (16–60%; see section 3.1), which is greater at higher VPD.

The response of the QNUT and CROPGRO models to mean temperature is shown in figure 8. Normalised yields are similar at low temperatures, but diverge at higher temperatures, beyond T_{opt}. QNUT shows increases in yield at super–optimal temperature. (Note the term super–optimal here refers to development rates and not to yields). These increases in yield are greater at higher temperatures, and also greater in the irrigated than the rainfed simulations. This is consistent with the mechanism for extended crop duration increasing yield for two reasons: firstly, duration is proportional to the exceedence of mean temperature over T_{opt}, and secondly, increased water availability allows the crop to take advantage of the increased season length.

The response of GLAM to mean temperature is also shown in figure 8. This response was calculated by taking the difference between the scenario and CO_2–only simulations.

Prior to differencing, yields were averaged over all grid cells within each location. (Hence this number is a measure of the distance between the solid and dotted lines in figure 4). Whilst GLAM shows increases in yield at super–optimal temperatures in three of the four locations, these locations are not entirely consistent with those seen in the QNUT results. In GLAM, for example, the response in NW is the lowest of the three. This is because of the high VPD in that region, which reduces yield more strongly in GLAM than in QNUT. On the whole, GLAM shows a greater response to mean temperature than QNUT. The sign of the temperature response in CROPGRO is the opposite to that of GLAM and QNUT. The reasons for this are discussed below.

4. Discussion

4.1. Bio–physical processes

In accordance with the first aim of this study, two bio–physical processes, which are not usually cited in climate change studies, have been identified. The first of these is that when the optimal temperature for development is exceeded, crop duration is lengthened and yield may increase. This was seen most markedly in GLAM, which used an optimal temperature for development of 28°C. The same effect was seen in QNUT (T_{opt}=29°C), in a manner proportional to the mean temperature in the climate change scenario (figure 8). However, increases in yield were not seen in the CROPGRO model (T_{opt}=28–30°C, depending on development stage). For some simulations, this was because the duration of the crop did not lengthen. For other simulations, there was an extension in duration resulting from the super–optimal temperatures, but this still did not result in greater yields. Since T_{opt} during pod filling is similar in CROPGRO to GLAM, this suggests that other processes in CROPGRO affected growth and development at high temperatures. For example, at high temperatures, the partitioning to pods in CROPGRO is decreased. CROPGRO also includes a temperature–dependent parameterisation of photosynthesis, so that, for example, in CE higher temperatures produced shorter durations but higher yields.

Crops exhibit a number of temperature thresholds which, when exceeded, result in reduced yield. For example, in some (but not all) genotypes, the temperatures encountered during flowering in this study can result in a reduction in fruit–set and yield, in spite of any lengthening of duration (Challinor et al., 2007a). This process was not simulated in any of models in this study. Vegetative growth may also be affected at high temperatures. In groundnut, vegetative growth is optimal at 30–35 °C (Ketring, 1986). This range is similar to the average temperatures seen in the regions where duration is lengthened in this study (figure 8). This suggests that changes in vegetative growth would be unlikely to greatly reduce the simulated yields reported in this study. Other high temperature processes, such as impacts on germination (Ong, 1986), may begin to mitigate the duration–induced increases in yield at temperatures far beyond ($\gtrsim 15$°C) T_{opt} (Squire, 1990). In this study, temperatures did not exceed T_{opt} by such large amounts. For example, less than 2% of the mean temperatures from sowing to maturity in GJ exceeded T_{opt}+7 (=35°C). Hence in terms of processes, the increases in yield simulated by GLAM at $T > T_{opt}$ seem plausible. The relevance of this result goes beyond just groundnut cultivation in India for two reasons. Firstly, this process is common to many tropical annual crops, and secondly temperatures under climate change are expected to increase across the tropics, not just in India.

Identification of the importance of super–optimal temperatures in determining yield is not new. Hammer et al. (1995) noted the lack of crop duration data at high temperatures. This is in part because of the difficulty in maintaining low levels of water stress at high temperatures. Also, at high temperatures lethal limits may be approached, making the isolation of the impact of temperature on development difficult.

The second process identified in this study is the reduction in transpiration efficiency at high values of VPD. This was seen most markedly in GLAM. It was seen consistently in QNUT, which uses transpiration efficiency, and a known assimilation (derived from radiation use efficiency) to calculate transpiration. Yield reductions were seen consistently in CROPGRO only when the Penman–FAO evapotranspiration method was used. This suggests that in both QNUT and CROPGRO, the mechanism for reducing yield was via water use, rather than via assimilation as in GLAM.

Is the simulated impact of VPD on yield a process that we may expect to observe in the field under climate change? Certainly, VPD is expected to increase under climate change, although the magnitude of the change may be uncertain (see section 2.2). The response of assimilation to VPD that is used in both GLAM and QNUT is based on observations that indicate an inverse relationship beyond a threshold VPD (e.g. Chapman et al., 1993;

Squire, 1990). Hence the process is certainly a real one. The basis for this relationship is discussed in more detail in Tanner and Sinclair (1983) and Kemanian et al. (2005). The relationship has been used successfully in a number of models, ranging from leaf–level photosynthesis models (Leuning, 1995) to larger scale analyses at the canopy/yield level (Zwart and Bastiaanssen, 2004). A number of process–based crop models also parameterise this relationship. In the most recent Wageningen model, GECROS (Yin and van Laar, 2005), the ratio of intercellular to atmospheric CO_2 concentrations decreases linearly with leaf–to–air VPD. Whilst the standard version of the CERES crop model (Jones and Kiniry, 1986) does not include the impact of VPD on assimilation, at least one version with VPD–dependence has been developed (Lizaso et al., 2005). Of the water use efficiency models which use this relationship that were reviewed by Tanner and Sinclair (1983), none had a threshold value of VPD below which assimilation was not affected. Hence at low VPD, these models would show a greater sensitivity than GLAM to increasing VPD.

Steduto and Albrizio (2005) found greater skill when normalising water–use efficiency by reference evapotranspiration (ET_{ref}), as opposed to VPD. Does the sensitivity to humidity depend upon the humidity metric used? For China, Gong et al. (2006) found that ET_{ref} was mostly controlled by relative humidity (followed by solar radiation and temperature). Since ET_{ref} is proportional to VPD, and rises also with temperature (Allen et al., 1998), it would be expected to rise under climate change. As a proxy for the change in ET_{ref} in the simulations in this study, the change in potential evapotranspiration was computed (ET_{ref} itself could not be calculated because of a lack of wind data). Potential evapotranspiration increased by 10–30% over most of central India. These increases are similar to those in VPD (see section 2.2), suggesting a similar impact on transpiration efficiency.

4.2. Uncertainty and its implications

The uncertainty in the response of yield to climate change in this study was comparable in magnitude to the mean simulated yield change (section 3.1). However, this does not prevent the results from suggesting some implications for future assessments of crop yield under climate change. Transpiration efficiency was a key uncertainty, consistent with the findings of Challinor et al. (2005a), as was its interaction with VPD. The results showed that changes in transpiration and in TE do not act systematically across space. Hence even when modelling assimilation and water use at the relatively large (canopy) scale, bias correction is problematic. This demonstrates the need for process–based modelling, since empirical methods cannot reproduce such non–linear interactions. For the same reason, this result demonstrates the need to take account of known uncertainties at the input stage of crop modelling, rather than only at the output stage.

In addition to the uncertainty due to assimilation and water use, then, there is an uncertainty associated with the interaction of simulated processes. Only for a crop model whose equations were 100% accurate (but with uncertainty in parameter values, due to measurement error) would the output uncertainty be a true reflection of the limitations of our measurements. Such a model would necessarily be a complex model with many input parameters. Uncertainty in each of these parameters will interact, resulting in a large uncertainty in yield. In reality any model will have structural uncertainty (its equations will not be 100% correct), so that the output uncertainty of a complex model will be both large and have its own associated uncertainty. A simple model has less parameters, and is likely to have a high fraction of directly measurable parameters. Therefore a simpler model is likely to have a lower output uncertainty estimate than a more complex model. However, a simple model is also less likely to contain all the relevant interactions and processes, so that it will probably underestimate uncertainty. Optimal complexity includes all key processes whilst minimising structural and parameter uncertainty.

The projected yield changes in the GLAM simulations often varied little in sign (figure 5). This is because they are explicable principally in terms of the two processes discussed in section 4.1. Where water was sufficient (CE and GJ), the probability of increases in the yield of the fixed–duration crop was high. Conversely, the probability was low for the well–watered variable–duration crop, as long as the optimal temperature for development was not exceeded. In regions where T_{opt} was exceeded, yields tended to increase, regardless of water availability (figure 5). Confidence in these results is greatest where T_{opt} is not exceeded, since GLAM is well–tested in this temperature range (Challinor et al., 2005c). However, a cross–model consensus did not emerge on the response at $T < T_{opt}$ (figure 8). Water–stressed regions (NW and SP) under the fixed–duration crop tended to show decreasing yield, even where water availability did not fall (cf figures 1 and 6). This is due primarily to the inverse relationship between VPD and yield. Without the indirect impact of elevated CO_2, yields in these regions show increases (CW07). Note that these regions also tend to have higher risk of heat stress damage (Challinor et al., 2007a), which also acts to reduce yields.

The analysis above has shown that under the SRES A2 scenario, in the absence of adaptation, CO_2 stimulation is more than offset by other processes — principally the impact of temperature on duration. How general is this result?. Some degree of generality would be expected across annual crops and across tropical regions, since the same bio–physical processes will occur. For India, studies of rice, wheat and soybean have shown that CO_2 stimulation is more than offset by warming (Mall et al., 2004; DEFRA, 2005). Whilst earlier studies have shown only a partial offset (Ministiry of Environment and Forests, Government of India, 2004), at least one review suggests that complete offset is likely (Easterling and Apps, 2005). Experimental studies support this. For example, Wheeler et al. (1996) found that the increase in wheat yield under doubled CO_2 is offset by a mean warming of less than 2°C. This is less than the projected change in any part of India in this study (figure 1). This result implies that the need for genotypic adaptation to mean temperature changes is critical (see also Challinor et al., 2007a).

5. Conclusions

This study has identified two processes which may be important in determining the yield of tropical annual crops under climate change. The moderation of duration by temperature and photoperiod is a fundamental and well–researched topic. However, responses above the optimum temperature for development have not been quantified as well as those below. More crop experiments to quantify the extension of duration through super–optimal temperatures, and the associated increase in yield, are required. The second process, the impact of low atmospheric humidity on assimilation, has been researched in depth in crop experiments. However, no consensus on this response was found in the crop models in this study. More analysis and more modelling studies would help to elucidate the likely importance of this process relative to other bio–physical climate change processes. Since projections of decreases in humidity under climate change are not confined to the tropics (see e.g. Rowell and Jones, 2006), this question is one of broad significance.

This study has also shown that the quantification of uncertainty does not preclude the identification of key processes. Neither does it preclude conclusions regarding the direction of likely changes in crop yield, given a particular climate change scenario. Indeed, more adequate quantification of uncertainty can lead to greater confidence in our assessments of the impact of climate change on crop yield. In this case — that of groundnut in India — we have shown that the beneficial direct impact of elevated CO_2 can be offset by indirect effects of climate change. This highlights the importance of genotypic adaptation to climate change. Finally, we note the role, illustrated here, of crop models of intermediate complexity in identifying processes and quantifying uncertainty.

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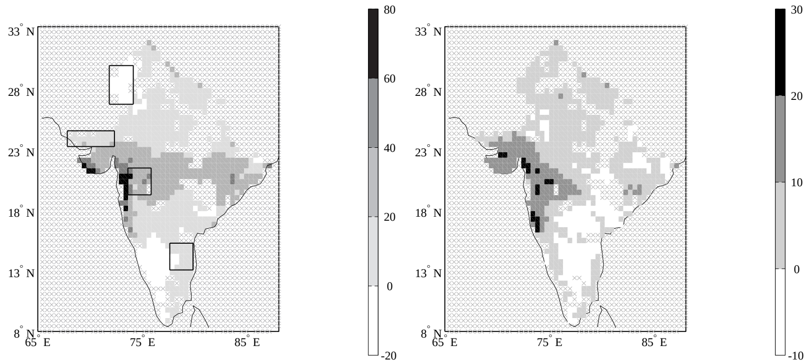
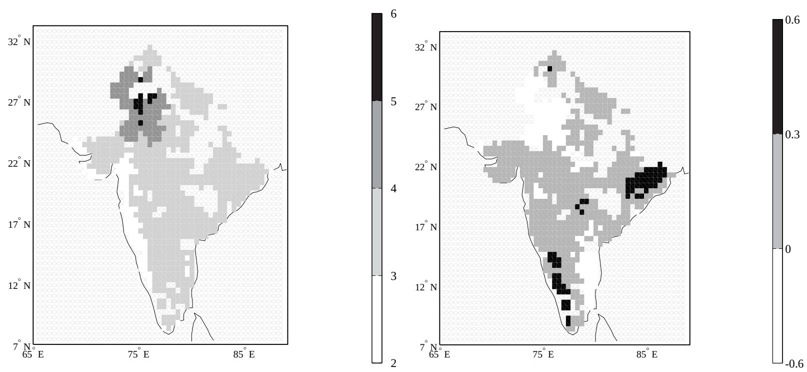
Table I. The 18 scenario simulations grouped by properties. Four of the crop model parameter variations affect simulation in both the baseline climate and the future climate (2071–2100) scenarios (there are therefore four corresponding baseline simulations — see text). Six of the parameter variations affect only the scenario simulations. Each unique pair of scenario parameter variations (Large/Small TE Increase, Reduced/Same SLA Limit) adds up to 18. The final two rows add up to 15, since the three Reduced VPD–TE Interaction scenario simulations had their own (small) value of the parameter controlling increases in TE at low VPD (see CW07). All scenario simulations used a value of the physiologically–limited maximum transpiration that was 17% lower than the corresponding baseline value.

	Baseline and Scenario	
Name	No. simulations	Description
Control	4	Standard parameter set
High Baseline TE	5	Increased transpiration efficiency
Reduced Physiological Transpiration Limitation	6	Increased physiologically–limited maximum transpiration
Reduced VPD–TE Interaction	3	TE is constant over a larger range of VPD
	Scenario only	
Name	No. simulations	Description
Large TE Increase	8	40% TE increase under 2^*CO_2
Small TE Increase	10	24% TE increase under 2^*CO_2
Reduced SLA Limit	12	10% decrease in prescribed maximum SLA under 2^*CO_2
Same SLA Limit	6	No change in prescribed maximum SLA under 2^*CO_2
No TE Increase at Low VPD	6	At low VPD, TE does not increase under 2^*CO_2
TE Increase at Low VPD	9	TE increases for all values of VPD under 2^*CO_2



(a) $\overline{P}$ (%)

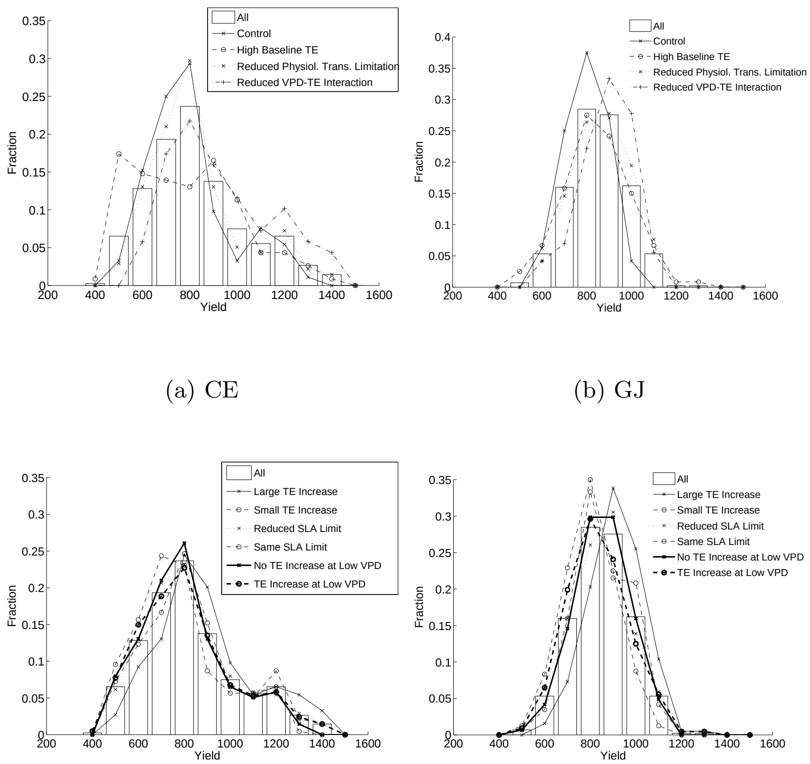
(b) σ_P (%)



(c) $\overline{T}$ (^{o}C)

(d) σ_T (^{o}C)

Figure 1. Change in the statistics (bars indicate means, σ indicates standard deviation) of growing–season weather (precipitation, P and mean daily temperature, T) between the 1961-90 baseline simulation and the 2071–2100 simulation. Crosses indicate regions where no simulations were carried out. Also shown are the four regions used for further analysis. From north to south, these are: NW, GJ, CE and SP



(a) CE

(b) GJ

(c) CE

(d) GJ

Figure 2. Ensembles of thirty–year mean yields from the 2071–2100 scenario simulations using individual grid cells within each of two regions (CE and GJ; see figure 1a). Each ensemble consists of a number of simulations grouped by crop model parameter values, as described in table I. (a) and (b) show the 18 simulations grouped by perturbations of baseline parameter sets (each group having various scenario parameter sets). (c) and (d) show the simulations grouped by perturbations of scenario parameter sets (each with a number of baseline sets).

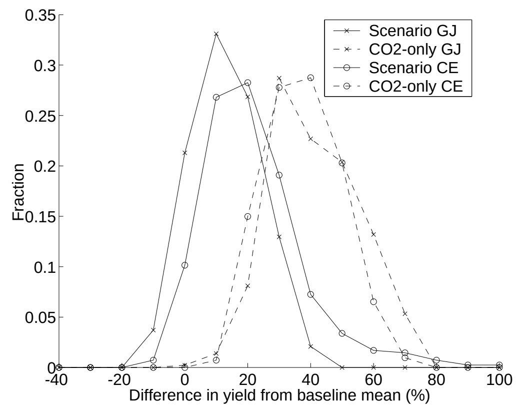


Figure 3. Simulations, within each of two regions, under two conditions: the baseline climate with elevated CO_2 (CO_2–only), and the 2071–2100 scenario. The latter uses the fixed crop durations, so that the time to maturity at each location is the same in both simulations. Differences between the two simulations are therefore due only to the indirect effects of CO_2 (excluding the impact of mean temperature on duration). Two regions, both with similar behaviour, are shown. In all cases, means of all 18 ensemble members have been used to calculate the histogram.

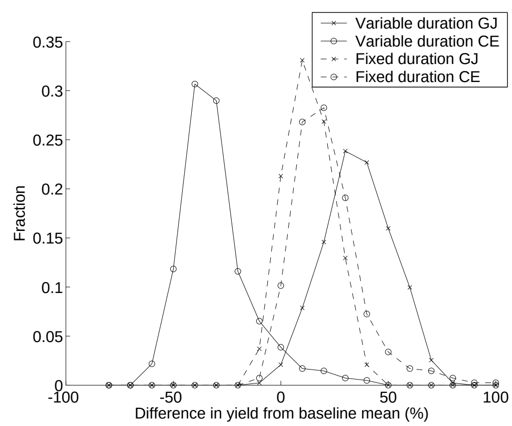
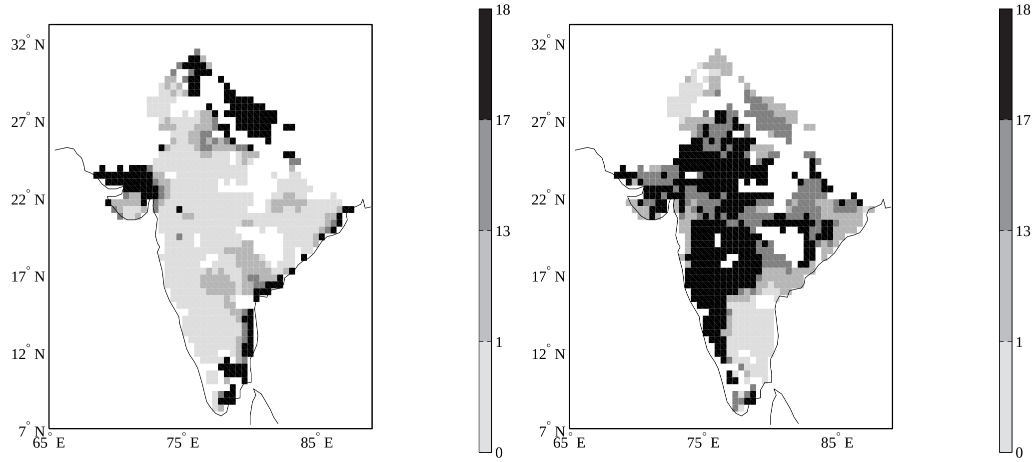
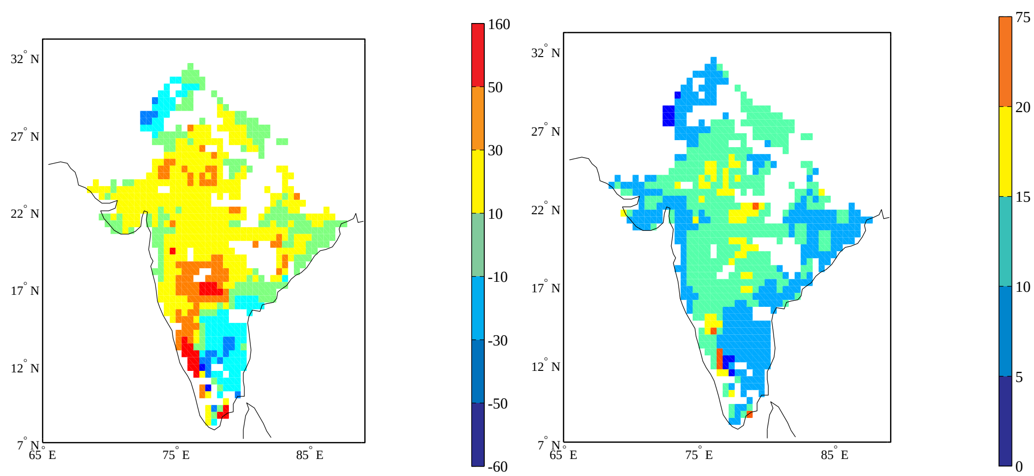


Figure 4. Fixed and variable duration simulations, within each of two regions, using the scenario climate. Two regions with contrasting behaviour are shown. In GJ the optimal temperature for crop development is exceeded, and in CE it is not. In all cases, means of all 18 ensemble members have been used to calculate the histogram.



(a) Variable duration (b) Fixed duration

Figure 5. The number of ensemble members, from a total of 18, which predict an increase in yields between the baseline and scenario periods. The results for the fixed–duration crop are very different to those of the variable duration crop.



(a) Mean (b) Standard deviation

Figure 6. Mean and standard deviation of the ensemble values of percentage change in yield between the baseline and 2071–2100 scenarios. The fixed–duration crop has been used for these simulations, so that any changes are due to changes in growth processes only.

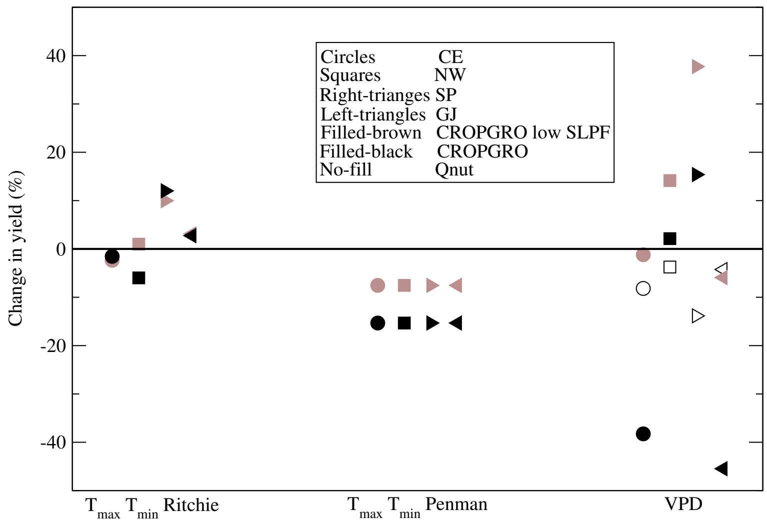


Figure 7. Results of the humidity sensitivity analyses, carried out on two crop models: the DSSAT CROPGRO model (D) and QNUT (Q). Four regions (CE, NW, SP and GJ) are shown. CROPGRO simulations used two values of the soil fertility factor, SLPF. Three sensitivity analyses on CROPGRO are shown. Two of these adjusted the maximum and minimum temperatures (+2 and -2 °C, respectively), whilst using either the Ritchie version of the Priestley–Taylor equation or the Penman–FAO method to calculate evapotranspiration. The third method adjusted VPD directly by multiplying it by 1.5. This third method was also used with QNUT.

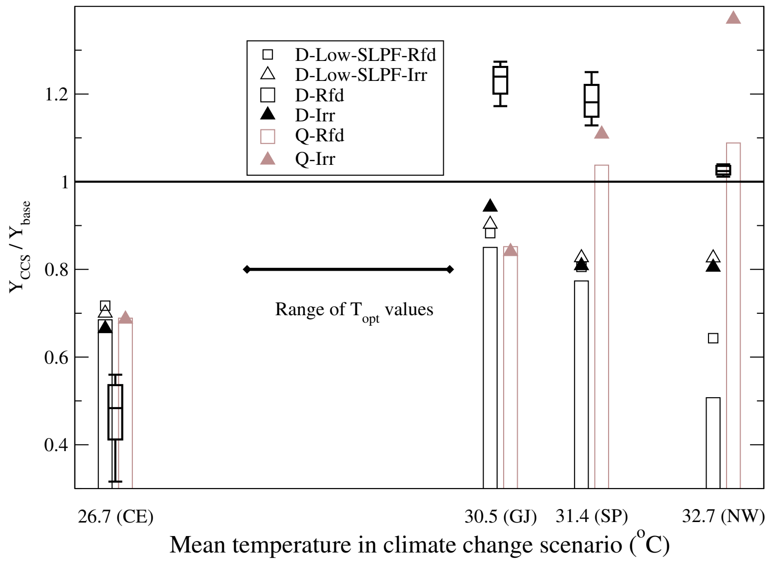


Figure 8. Results of the temperature sensitivity analysis, carried out on two crop models: the DSSAT CROPGRO model (D) and QNUT (Q). Yields for the climate change scenario (CCS) were simulated using no CO_2 increase, so that only changes in climate affected the simulations. Rainfed (Rfd) and irrigated (Irr) runs are shown. CROPGRO simulations used two values of the soil fertility factor, SLPF. All CROPGRO simulations used the Ritchie calculation of evapotranspiration, as this the option which minimises any systematic influence of VPD (see figure 7). The 18 GLAM ensemble members are also shown as boxplots (whiskers show full range, boxes show inter–quartile range, and bars show median). These GLAM simulations have been corrected for the impact of increased CO_2, as described in the text. Mean temperature changes were calculated over the first 90 days of crop growth. In the baseline simulations, the corresponding temperatures are, from left to right, 23.8, 27.4, 27.9 and 27.9 °C. These last three temperatures are close to the range of optimal temperatures for development (T_{opt}) across all three crop models.

List of abbreviations

CW07	Challinor and Wheeler (2007)
GLAM	General Large–Area Model for annual crops
LAI	Leaf area index
SLA	Specific leaf area
TE	Transpiration efficiency
VPD	Vapour pressure deficit

Appendix

A. List of scenario simulations

Table II. The 18 scenario simulations, described in terms of the four parameter properties listed in table I: the baseline parameter set to which changes were applied and the imposed changes, under elevated CO_2, in transpiration efficiency (TE) and maximum specific leaf area (SLA).

Baseline	**TE increase**	**Max. SLA**	**TE increase at low VPD**
Control	Small	Unchanged	Yes
Control	Small	Decreased	Yes
Control	Large	Decreased	No
Control	Large	Decreased	Yes
High Baseline TE	Small	Unchanged	No
High Baseline TE	Small	Decreased	No
High Baseline TE	Small	Unchanged	Yes
High Baseline TE	Small	Decreased	Yes
High Baseline TE	Large	Decreased	No
Reduced Physiological Transpiration Limitation	Large	Decreased	Yes
Reduced Physiological Transpiration Limitation	Small	Unchanged	No
Reduced Physiological Transpiration Limitation	Small	Unchanged	Yes
Reduced Physiological Transpiration Limitation	Small	Decreased	Yes
Reduced Physiological Transpiration Limitation	Large	Decreased	Yes
Reduced Physiological Transpiration Limitation	Large	Decreased	No
Reduced VPD–TE Interaction	Small	Decreased	Small decrease
Reduced VPD–TE Interaction	Large	Unchanged	Small decrease
Reduced VPD–TE Interaction	Large	Decreased	Small decrease

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