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Quantification of physical and biological uncertainty in the simulation of the yield of a tropical crop using present day and doubled CO_2 climates

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Abstract

The impacts of climate change on crop productivity are often assessed using simulations from a numerical climate model as an input to a crop simulation model. The precision of these predictions reflects the uncertainty in both models. We examined how uncertainty in a climate (HadAM3) and crop (GLAM) model affects the mean and standard deviation of crop yield simulations in present and doubled CO_2 climates by perturbation of parameters in each model. The climate sensitivity parameter (λ, the equilibrium response of global mean surface temperature to doubled CO_2) was used to define the control climate. Observed 1966–1989 mean yields of groundnut (*Arachis hypogaea* L.) in India were simulated well by the crop model using the control climate and climates with values of λ near the control value.

The simulations were used to measure the contribution to uncertainty of key crop and climate model parameters. The standard deviation of yield was more affected by perturbation of climate parameters than crop model parameters in both the present day and doubled CO_2 climates. Climate uncertainty was higher in the doubled CO_2 climate than in the present day climate. Crop transpiration efficiency was key to crop model uncertainty in both present day and doubled CO_2 climates. The response of crop development to mean temperature contributed little uncertainty in the present day simulations but was amongst the largest contributors under doubled CO_2. The ensemble methods used here to quantify physical and biological uncertainty offer a method to improve model estimates of the impacts of climate change.

Keywords

Crop yield, climate change, model uncertainty

Short title: Uncertainty in crop yield simulation in present day and doubled CO_2 climates

1 Introduction

Global food production is expected to change considerably due to climate change over the coming century (Parry et al., 2004). Assessments of the impacts of climate change on the productivity of crops employ crop models to predict crop yields under scenarios of climate change that are provided from general circulation models (GCMs). Often, predictions of the impact of climate on crop yields will vary according to which GCM and/or crop model is used. For example, Matthews and Wassmann (2003) predicted rice productivity across Asia under doubled current atmospheric CO_2 concentrations using two crop models and three GCMs. The magnitude of yield changes that were predicted differed between the crop models, and the sign of the yield change was affected by the GCM scenario. The reasons for such differences among crop and climate model predictions need to investigated further in order to improve our assessment of the impacts of climate change.

Uncertainty in climate change impacts assessments comes from a number of sources. Future emissions of greenhouse gases must be estimated, and the response of both the atmosphere and the impact in question have associated uncertainties. There is no consensus in the literature to date on how best to quantify these uncertainties. In the case of agricultural yield, the range of values across sites and/or climate change scenarios is often used (e.g. IPCC, 2001a; Tubiello et al., 2002; Trnka et al., 2004). As a result of the differences in methods, uncertainty ranges are not directly comparable. Different studies take account of different uncertainties. For example, Reilly and Schimmelpfennig (1999) projected changes of -98% to +16% for maize in Africa (range across sites and climate scenarios); Jones and Thornton (2003) projected a change of -17% for maize in Zimbabwe. In addition, the large range of possible crops and locations means that the number of directly comparable studies is small. Hence any consensus from the literature on likely future agricultural yield is being reached by random sampling of the many uncertainties.

This study is a first step towards quantifying the uncertainty in agricultural yield projections by looking at the fundamental biological and physical processes involved. The methods used are consistent with the recommendations of Katz (2002): assessing uncertainty of individual model components separately, and applying uncertainty analysis to simpler impacts models in order that the mechanisms by which uncertainty propagates can begin to be understood.

1.1 Physical, biological and anthropogenic uncertainty

Physical uncertainty, for given levels of greenhouse gas and aerosol emissions, comes from a number of sources (IPCC, 2001b). Firstly, imperfect knowledge of the impact of emissions on the radiation balance means that the extra heat input to the atmosphere is not known precisely. It is not only atmospheric composition that plays a role: changing land use will also impact the radiative budget. Secondly, there is a range of plausible atmospheric responses to the change in radiative forcing. Estimates of this range are constrained by limited computer resources. This is most evident in the relatively coarse spatial resolution of GCMs.

Anthropogenic uncertainty is the result of imperfect knowledge of crop management decisions such as the choice of crop and variety, irrigation and fertiliser application, and planting date. For example, improvements in yields over time due to the release of new varieties usually results in a monotonically increasing trend in yield. As with all management–related factors, this may vary in both space and time (e.g. Kulkarni and Pandit, 1988; Moss and Shonkwiler, 1993). Despite these uncertainties it is still possible to simulate yields with some accuracy using observed large–area gridded data (e.g. Challinor et al., 2004).

Biological uncertainty results from the range of plausible responses of the crop to the climate. It is not only climate over the season that has an impact on crop growth and development; the statistics and timing of the weather within the season are also crucial (e.g. Wright et al., 1991; Wheeler et al., 2000). The uncertainties associated with the simulation of these processes depend upon the spatial scale of the investigation (e.g. Hansen and Jones, 2000). For example, the impact of terrain slope may be small when averaged over large areas, but considerable at smaller scales. Even over large areas, the relationship between crop yield and climate is complex and can change over time. For example, Challinor et al. (2005c) found that the relationship between June-to-September rainfall and groundnut yield for a 0.5 degree grid cell in Andhra Pradesh, India, changed between the periods 1966–77 and 1978–89: the correlation coefficient increased from -0.13 to +0.58.

There is also a direct response of the crop to increased carbon dioxide. A review of 18 crop species under controlled environments (Kimball and Idso, 1983) suggested that water use efficiency may double with a doubling of CO_2. Based on controlled environment studies of groundnut (Clifford et al., 2000), transpiration efficiency for doubled CO_2 could increase by between 50 and 100%. Controlled environment experiments also show that changes in water use under doubled CO_2 at the canopy level are of the order of 10–30% for C3 crops (e.g. Allen Jr. et al., 2003; Kimball and Idso, 1983), with the greater reductions being associated with greater increases in transpiration efficiency. Free–air CO_2 enrichment (FACE) experiments (see e.g. Ainsworth and Long, 2005) have shown that in a field environment, the reduction in water use may be nearer to 3–7% (Kimball et al., 2002). These experiments inform the simulation of the CO_2 fertilisation effect (e.g. Tubiello and Ewert, 2002). The modelling study of Ewert et al. (2002) assumed a linear reduction in crop transpiration up to 10% at doubled CO_2.

Simulation models provide a tool for the quantification of variables and their associated uncertainty. The uncertainty in the response of the atmosphere to a doubling of CO_2 has been assessed by comparing the results of different GCMs (IPCC, 2001b) and by varying parameters within a single GCM (Murhpy et al., 2004). Hence uncertainty due to both model structure and model inputs can be assessed. There are fewer examples of this type of comparison within the crop modelling literature, perhaps because there is already significant uncertainty in the climate change scenarios used as inputs. Mearns et al. (1999) found significant differences in the response of two process–based crop models to a doubling of CO_2.

1.2 Scope of this study

This study focusses principally on the bio–physical uncertainty in estimates groundnut (i.e. peanut; *Arachis hypogaea* L.) yield in India with CO_2 at double present–day levels. A single GCM and a single process–based crop model are used to estimate the uncertainty in the response of yield to a doubling of CO_2. The uncertainty due to model formulation is not treated, since the focus is on the uncertainty due to the range of plausible parameter values in both the crop and the climate models. Parameters are varied one at a time, so that interactions between crop and climate model uncertainties are not considered; rather, this is a first estimate of the relative magnitude of the crop and climate modelling uncertainties. The one exception to this is the parameters that determine the crop response to high temperature stress: two sets of high temperature stress parameter values were used with each climate ensemble member (see section 2.2).

2 Method: quantification of physical and biological uncertainty

2.1 Modelling methods

The General Large–Area Model for annual crops (GLAM)

The General Large-Area Model for annual crops (GLAM; Challinor et al., 2004) has been designed specifically for use within a combined crop and climate forecasting system; it capitalises on the predictability suggested by large–area relationships between climate and crop yield (Challinor et al., 2003). GLAM is a process–based model that is easily adaptable to most annual crops. The model operates on a daily time step using twenty crop-specific parameters and five additional parameters which vary spatially. Temperature, radiation, rainfall and humidity are used to simulate yields at a given technology level; increases in yield due to the mean impact of improvements in crop variety and management techniques are not simulated.

The planting date is determined by the model as the first day within a defined planting window in which the soil moisture exceeds a specified threshold. The timing of subsequent development of the crop through flowering, pod–filling and harvest is determined by thermal time relations. A soil moisture balance together with simulated roots allows potential water uptake to be calculated. Atmospheric conditions determine the evaporative demand, allowing water stress to be simulated. Leaf growth is the result of a potential rate modified by water stress. An independent calculation of biomass, via a transpiration efficiency, allows specific leaf area to be used as an internal consistency check. A constant rate of change of harvest index, from the pod–filling stage onwards, determines end–of–season harvest index, which is then used to calculate yield.

GLAM has successfully been been used to simulate groundnut yield in India using observed gridded data (Challinor et al., 2004), reanalysis data (Challinor et al., 2005c) and probabilistic seasonal hindcast output from GCMs (Challinor et al., 2005a). The soil data for these studies, and for the current study, come from FAO/Unesco (1974) and the data on planting dates from Reddy (1988). The planting window was given a broad width of one month, with crisis sowing being simulated once this period has passed. The planting window was not changed for the doubled CO_2 simulations; the vast majority of changes in simulated planting date (mean and standard deviation) between the two climates were less than six days, much smaller than the planting window itself.

GLAM uses a Yield Gap Parameter (YGP) which acts on the maximum rate of change of leaf area index. This is a simple method of simulating the impact of pests, diseases and non–optimal management on the crop. YGP is also the parameter used for calibration and it can correct for climate bias (Challinor et al., 2005a). To the extent that it can account for bias in the input rainfall, it can also account for bias in available soil water, and hence bias in the soils parameterisation.

Climate simulations

The climate simulations used are those of Murhpy et al. (2004). In that study HadAM3 was coupled to a mixed layer ocean and equilibrium present–day and doubled CO_2 simulations were carried out. For both of these cases parameters were varied one a time, relative to the standard (control) set of parameters. The 29 parameters chosen for this represent key sub–grid physical processes as either logical switches, variable coefficients or thresholds. Parameters were varied one at a time with a minimum and maximum value being used for variable coefficients. These values were chosen by seeking expert opinion. This procedure resulted in 53 perturbed physics simulations for both present–day and doubled CO_2 climates. The climate sensitivity parameter (λ), defined as the equilibrium response of global mean surface temperature to doubled CO_2, was calculated for each pair (present day and doubled CO_2) of simulations.

Four simulations from the twelve available at the time of the study were chosen such that a broad range of values of λ was represented. The chosen simulation perturbed parameters from the large–scale cloud, sea ice or convection schemes (table 1). A histogram of the values of λ from all 53 simulations is presented in figure 1. The control simulation (C) has a value of λ within the most populated interval of this histogram. The simulations designated $\lambda1$ and $\lambda2$ have values that are close to the control, and $\lambda3$ was chosen as a more extreme and less probable value.

2.2 Choice of crop model parameters

2.2.1 Crop model calibration

The yield data for calibration of the model came from the district–level database of agricultural returns compiled by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Patancheru, India. Districts range in size from less than 1km^2 to 46,800km^2, although there are only two districts which are less than 690 km^2 in area. The average of all district sizes is 8,300 km^2. The yield time series (1966–1989) for each individual district were linearly detrended to 1966 levels, in order to remove the influence of improved varieties and management methods. Yield data were then upscaled to the crop model grid using an area–weighted mean by assuming that the area under cultivation is spread evenly throughout each district.

The calibration procedure varied YGP in steps of 0.05 between 0.05 and 1, as for previous studies (e.g. Challinor et al., 2005a). Optimal values were defined as those which minimised the difference between the simulated twenty–year mean yield at that site and the observed 1966–1989 mean yields described above. This procedure was carried for each of the present–day climate simulations ($\lambda1$, $\lambda2$, $\lambda3$ and C) using the non–perturbed set of crop model parameters. In this way the impact of climate biases was minimised (see section 2.1).

2.2.2 Perturbation of crop model parameters in the present–day climate

The perturbation of parameters for GLAM used similar methods as those for the climate simulations: parameters were varied one at a time to either a minimum or a maximum value, so that an ensemble of realisations of yield was produced. The parameters chosen were those that previous studies showed to have a large impact on yield when varied within the ranges determined by independent observations (see Challinor et al., 2004). The list of parameters, which is presented in table 2, was chosen to give a broad representation of uncertainty in the response of the crop to climate (i.e. response to mean and high temperatures, radiation and water) and in the representation of crop physiology itself.

Perturbed parameter values were determined using the simulations of Challinor et al. (2005c). As part of that study GLAM parameter values were calculated which minimised root mean square error (RMSE) for time series of groundnut yield across India. These values vary spatially and it is the standard deviation of that variability, added to and subtracted from the mean, that forms the perturbed parameter values for the present–day climate simulations. All of the perturbations fall within observational constraints (see Challinor et al., 2004). The non-perturbed parameter values are those of (Challinor et al.,

2004) except where noted otherwise.

2.2.3 Perturbation of crop model parameters in the doubled CO_2 climate

The same perturbations as in the present–day climate were used for the doubled CO_2 climate, with one exception: the transpiration efficiency was changed in order to simulate the direct response of the crop to increased CO_2 levels. Associated changes in water use were also made. The two GLAM additional parameter perturbations used in the doubled CO_2 simulations (referred to as control and high–TE) are listed in table 3. The parameter values given are derived from the studies reviewed in section 1.1. The reduction in transpiration was implemented via a reduction of the calibrated present–day climate maximum transpiration rate (0.3 cm day^{-1}; Challinor et al., 2004). Use of this parameter ensures that the reduction in transpiration of water–stressed crops is less than that on well–watered crops, as is seen in observations (Kimball et al., 2002).

The chosen parameter values reported above correspond to a change in transpiration efficiency from the calibrated present–day non–perturbed climate value (table 2), of +24% and +100%. The maximum transpiration rate chosen for each of these values were 5% and 30% less than the present–day climate value, respectively (table 3). This ensures physiological consistency between these two parameters by excluding the combinations where transpiration efficiency and maximum transpiration rate are both high.

The indirect impact of CO_2 concentration changes is simulated by GLAM through the usual pathways: changes in temperature, rainfall, humidity and radiation will affect the crop simulations (Challinor et al., 2004). The high temperature stress parameterisation for GLAM (Challinor et al., 2005b) simulates the impact on pod–set, and subsequently yield, of high temperatures during the period when the crop is flowering. This parameterisation was designed with climate change in mind, since high temperature stress events are likely to be more frequent in future climates (Wheeler et al., 2000). The use of varieties which are either tolerant or sensitive to heat stress (table 2) can be thought of either as representing uncertainty in the response of the crop to these events, or as potential adaptive choices for farmers.

2.3 Analysis methods

The perturbations to physical and biological parameters in present–day and doubled CO_2 climates described above allow a preliminary assessment of contributions to uncertainty in yield simulation. Using the present–day climate simulations, differences between crop yields from perturbed and control runs indicate which bio–physical parameters currently contribute most to uncertainty. A similar analysis using only doubled CO_2 simulations indicates whether or not these contributions are likely to change. Finally, differences between the control present–day simulation and doubled CO_2 simulations provide estimates of the climate change signal.

Yield simulations where the crop failed to meet its thermal time requirement (see section 2.1) were omitted from all analyses. This leads to the removal in some cases of one grid cell in the north of the domain.

Four statistics were used to summarise the uncertainty associated with crop and climate model parameters (section 3.2). Two of these are based on percentage differences, from the control simulation, in the mean yield. The remaining two are based on percentage differences in the standard deviation of yield. For each of these two cases the variability across grid cells was quantified in two ways, both chosen to minimise sensitivity to extreme values: firstly the median value is a measure of spatially systematic differences between simulations. Secondly, the inter–quartile range is a measure of the non–systematic differences (i.e. the spatial variability of the response to the parameter pertubation). All four statistics produce one value per parameter pertubation.

3 Results

3.1 Calibration and simulation in present–day climate

The calibration proceedure (section 2.2) resulted in values of YGP that were broadly similar across the control, $\lambda 1$ and $\lambda 2$ simulations, with $\lambda 3$ showing greater differences. For $\lambda 1$, 7 out of 35 grid cells had values that differed from those of the control simulation by more than 0.05. For $\lambda 2$, this figure was 10, and for $\lambda 3$ is was 17. In addition, the values were on the whole greater in magnitude in the $\lambda 3$ case: the majority were greater than 0.5.

Figure 2 shows the level of agreement between the four simulations and the observed mean yield. Results are presented only for grid cells where there is a minimum total of twenty district–level observations contributing to the observed mean yield. This avoids the fitting of YGP to give apparently accurate simulations based only only a few data points. It results in the omission of the eastern–most grid cell. The $\lambda 3$ simulation has a notably higher error in the simulation of mean yield than the other three simulations. The high error in the two grid cells in the north–west in all four runs is due to low seasonal precipitation totals (< 140mm in all cases).

Given the ability of GLAM to simulate groundnut yield in India using observed gridded data Challinor et al. (2004), the relatively poor performance of $\lambda 3$ suggests that, at least for parts of India, this climate is less consistent than the other three climates with observed groundnut cultivation in India.

3.2 Quantification of uncertainty

The results presented in this section use percentage differences between perturbed parameter simulations and control simulations, as described in section 2.3. Figure 3 shows histograms of the differences in present day mean yield for two crop parameter perturbations and two climate model perturbations. The crop model parameter pertubations have a more narrow and displaced curve, indicating a more spatially systematic impact on yield.

Table 4 summarises the statistics of the remaining histograms (not shown) for the present day climate. The crop parameter perturbations tend to have lower inter–quartile range (IQR) than the climate parameter pertubations, indicating, as in figure 3, a more systematic impact on yield. In the case of mean yield ($\overline{Y}$) the magnitude of this systematic impact (as measured by the median difference across grid cells) is greater for some crop parameters than it is across climate pertubations. For standard deviation in yield (σ_Y) this is not the case, although transpiration efficiency and extinction coefficient do contribute significant uncertainty. In all cases the climate uncertainty is greater for σ_Y than for $\overline{Y}$ and it is reduced if $\lambda 3$ is excluded from the analysis.

Table 5 presents the equavalent results for the doubled CO_2 climate. These results are broadly similar to those of the present–day climate with some notable exceptions: optimal temperature is more important in determining the distribution of yield over both time and space (i.e. the IQR and median for both σ_Y and $\overline{Y}$ increase considerably for this parameter). Secondly, transpiration efficiency is more important in determining the variability in σ_Y and $\overline{Y}$ across space (i.e. the IQR is higher). Finally, the uncertainty associated with climate simulation is higher in this climate than in the present–day climate for all four statistics.

3.3 Yield changes under doubled CO_2

In all four present–day climate simulations there is very little incidence of high temperature stress (see section 2.2): all four simulations show less than four grid cells with more than one year where pod–set is less than 60% (the value below which yield is affected in the TOL case). For the doubled CO_2 case this figure rises in all four simulations. For the C, $\lambda 1$ and $\lambda 2$ this increase is modest: 2–5 grid cells are affected. However, in $\lambda 3$, most grid cells become affected, and the mean percentage of pods setting becomes seriously reduced. Figure 4 shows the extent of this reduction for both a sensitive (SEN) and tolerant (TOL) groundnut variety. Most of India is affected, although less area is affected in the TOL case than in the SEN case. The magnitude of the impact is greater for SEN than for TOL, showing the increased vulnerability of yield to high temperature stress when this type of variety is used.

Figure 5 presents the impact of the doubled CO_2 climate on the mean and standard deviation of yield for both the control and the $\lambda 3$ simulations. The difference between these two cases is marked; in particular, the sign of the change in standard deviation is different over large parts of India. Among the reasons for this might be the increase in the standard deviation of precipitation over most of India in $\lambda 3$. The corresponding changes in the control case are much less marked. A detailed analysis of causality is beyond the scope of this study.

A great deal of analysis of the impact of doubling CO_2 could be carried out using the simulations in this study. For the purposes of this paper, further analysis is restricted to some general observations. Changes in mean yield from present day values in the $\lambda 1$ and $\lambda 2$ simulations are broadly similar to the control case. Changes in the standard deviation of yield are higher in $\lambda 2$ than in the control. The increase in transpiration efficiency in the high–TE simulation compensates for the reduction in yields seen over central India in the control case (figure 5), resulting in little change in mean yield in that region. Finally, the choice of optimal temperature, noted in section 3.2 as being critical for the doubled CO_2 climate, has an impact comparable to the choice of climate ($\lambda 3$ or control).

4 Discusion and conclusions

The results presented above highlight the importance of uncertainty when estimating the response of both the mean and variability of crop yield to doubled CO_2. The contribution of climate uncertainty, particularly to the uncertainty in the estimation of yield variability, can be considerable. Also, the contribution of climate uncertainty was shown to be higher in the double CO_2 climate than in the present day climate (tables 4 and 5). The impact of the more extreme, less probable, response to CO_2 ($\lambda 3$) on the standard deviation of yield is large, and acts through two mechanisms: climate variability (figure 5), and high temperature stress (figure 4). The impact of climate uncertainty is smaller when this climate simulation is excluded from the analysis.

The importance of further constraining some of the GLAM parameters in present–day and doubled CO_2 climates has also emerged from this study. The transpiration efficiency is the principle source of uncertainty in the present–day climate, whilst the temperature increases associated with doubled CO_2 make the determination of optimal temperature important in that climate. This has relevance beyond that of crop yield simulation using this particular crop model: an understanding of the response of crop duration to increasing temperature is important in any yield impact assessment. The magnitude of the CO_2 fertilisation effect (mediated in GLAM via the transpiration efficiency) is also important under doubled CO_2, and can make the difference between yield increases and yield decreases (section 3.3). Further experiments under realistic field conditions (e.g. FACE) are needed in order to constrain estimates of CO_2 fertilisation (see Long et al., 2005).

Ensemble methods such as those used in this study provide a way to quantify physical and biological uncertainty. The methods can be extended to quantify anthropogenic uncertainty and/or look at adaptation strategies, by examining the use of different crops and management techniques (see also Dessai and Hulme, 2004). More rigorous probabilistic results can be obtained by using larger ensembles. Also, the obervational constraints on the parameter pertubations can be accounted for by comparing the resulting climate and crop quantities (yield, specific leaf area, biomass) to observations. There is already evidence to suggest that the probabilistic nature of climate forecasting on seasonal timescales can be exploited to provide useful information on crop productivity (e.g. Cantelaube and Terres, 2005; Challinor et al., 2005a; Marletto et al., 2005; Hansen and Indeje, 2004). Accepting and quantifying the uncertainty associated with climate change may bring similar skill, and has the further advantage of identifying key sources of uncertainty. These methods clearly have the potential to improve vastly on the single–scenario methods commonly used to identify climate change impacts.

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Simulation name	Parameter	λ (°C)
C	Sea ice albedo	3.60 ± 0.05
$\lambda1$	Cloud droplet to rain conversion rate	2.91 ± 0.06
$\lambda2$	Ice fall speed	4.10 ± 0.05
$\lambda3$	Entrainment rate coefficient	6.98 ± 0.04

Table 1: The QUMP simulations used in this study. The GCM parameters shown were perturbed, resulting in different values of the climate sensitivity parameter, λ.

Parameter	Units	Impact	Non-perturbed	Pertubation
Rate of change of harvest index	day^{-1}	Biomass partitioning	0.007	0.001
Extinction coefficient	—	Available radiation	0.55[1]	0.17
Optimum temperature	°C	Development; response to mean temperature	28.0	1.8
Transpiration efficiency	Pa	Response of biomass to water	1.51[1]	0.47
High temperature stress parameters	—	Response to temperature extremes	No response	TOL or SEN

Table 2: GLAM parameter pertubations for the simulations of present–day climate. The three sets of runs carried out for each parameter correspond to the non-perturbed value and the non-perturbed value plus, and minus, the pertubation. [1] indicates that non-perturbed values differ from those of Challinor et al. (2004) In both cases these differences are less than or equal to 10%. The TOL and SEN parameter sets representing tolerant and sensitive varieties, respectively, are taken directly from Challinor et al. (2005b)

Parameter	Units	Impact	Control	High–TE
Transpiration efficiency	Pa	Water use efficiency	1.87	3.02
Max. transpiration rate	cm day^{-1}	Absolute water use	0.285	0.210

Table 3: GLAM parameters used in the doubled CO_2 simulations. Either the control or high–TE parameter set was used. The additional parameters and ranges listed in table 2 were also used for these simulations.

	Median		Inter–quartile range	
Variable	$\overline{Y}$	σ_Y	$\overline{Y}$	σ_Y
Rate of change of harvest index	-14 & 14	-14 & 14	0 & 0	0 & 0
Extinction coefficient	-24 & 17	-27 & 19	19 & 18	17 & 18
Optimal temperature	-1 & 6	0 & 2	3 & 20	4 & 24
Transpiration efficiency	-30 & 26	-28 & 24	2 & 5	7 & 13
$\lambda1$, $\lambda2$, $\lambda3$	-11 to 5	5 to 46	14 to 49	48 to 284
$\lambda1$, $\lambda2$	-2 & 5	5 & 18	14 &19	48 & 54

Table 4: Statistics of the percentage difference in the present–day climate between the perturbed–parameter simulations and the control simulation. The median and the inter–quartile range across grid cells are shown for both the twenty–year mean yield ($\overline{Y}$) and the standard deviation over that period (σ_Y).

	Median		Inter–quartile range	
Variable	$\overline{Y}$	σ_Y	$\overline{Y}$	σ_Y
Rate of change of harvest index	-14 & 14	-14 & 14	0 & 0	0 & 0
Extinction coefficient	-22 & 13	-23 & 13	17 & 20	22 & 24
Optimal temperature	-19 & 43	-19 & 60	23 & 24	55 & 62
Transpiration efficiency	25	24	13	39
$\lambda1$, $\lambda2$, $\lambda3$	-2 to 23	-22 to 58	25 to 66	40 to 438
$\lambda1$, $\lambda2$	-2 & 6	-22 & 34	25 & 31	40 & 70

Table 5: Statistics of the percentage difference in the doubled CO_2 climate between the perturbed–parameter simulations and the control simulation. The median and the inter–quartile range across grid cells are shown for both the twenty–year mean yield ($\overline{Y}$) and the standard deviation over that period (σ_Y).

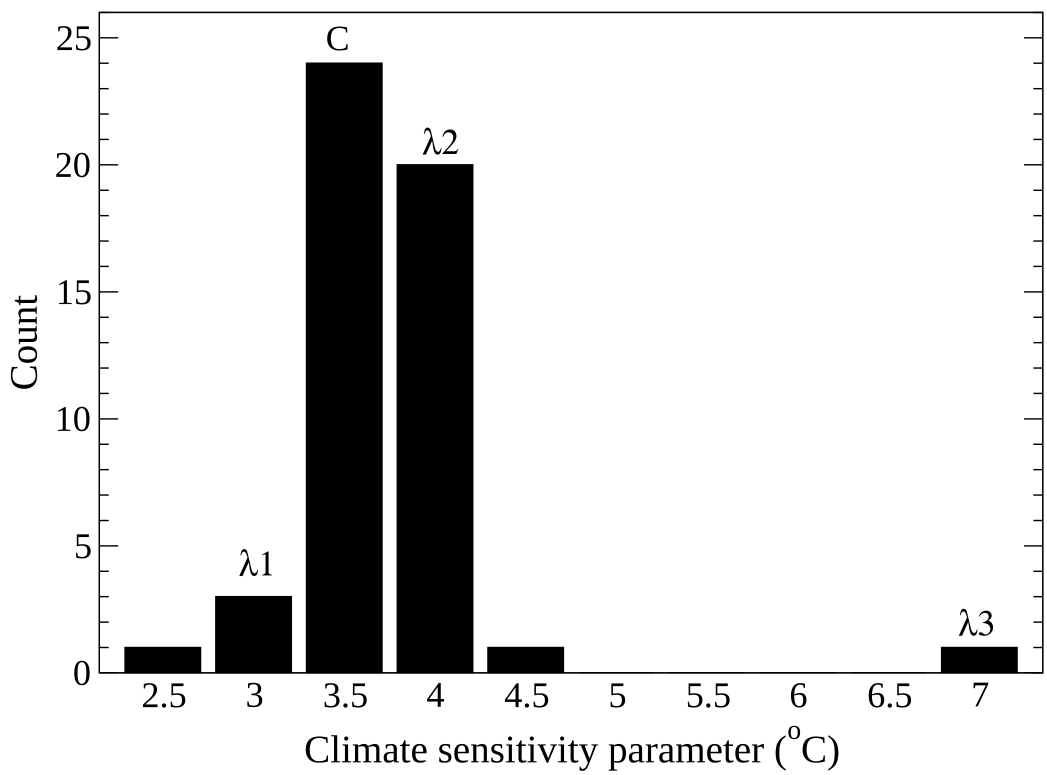
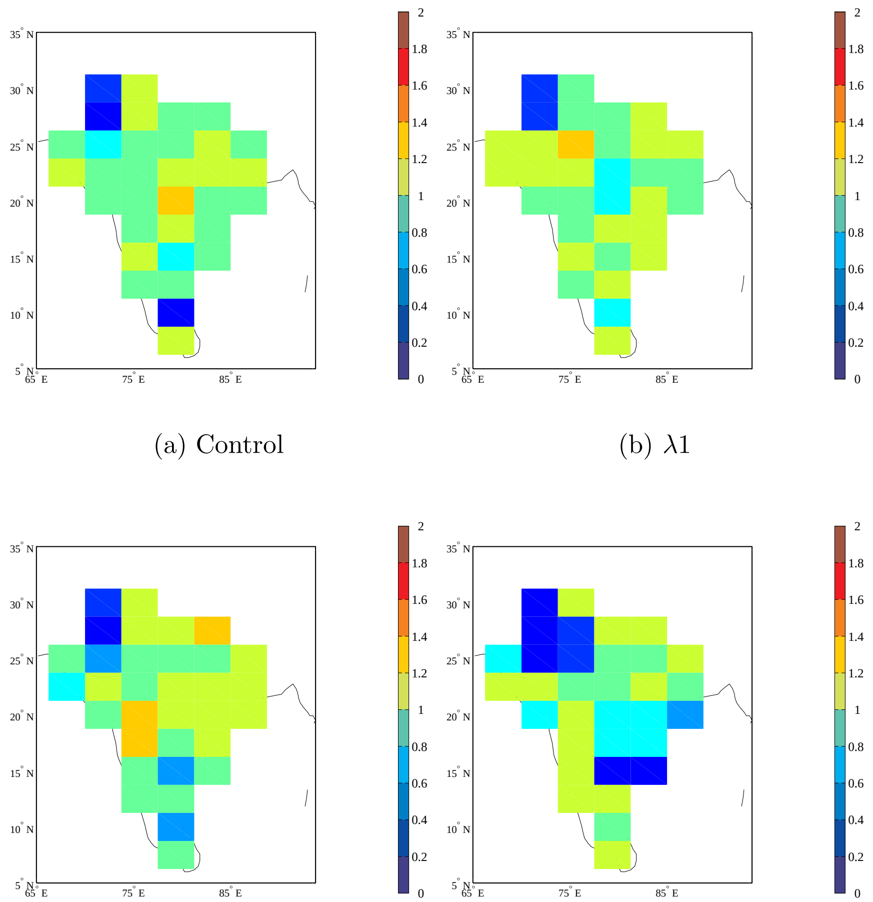


Figure 1: Histograms of the values of the climate sensitivity parameter (λ) resulting from the 53 QUMP ensemble members. Labels show the location of the simulations used in this study: the control simulation (C) and three pertubations ($\lambda1$–$\lambda3$).



(a) Control

(b) $\lambda1$

(c) $\lambda2$

(d) $\lambda3$

Figure 2: Twenty–year mean of the simulated yields for the four present–day climate pertubations, normalised by the observed values.

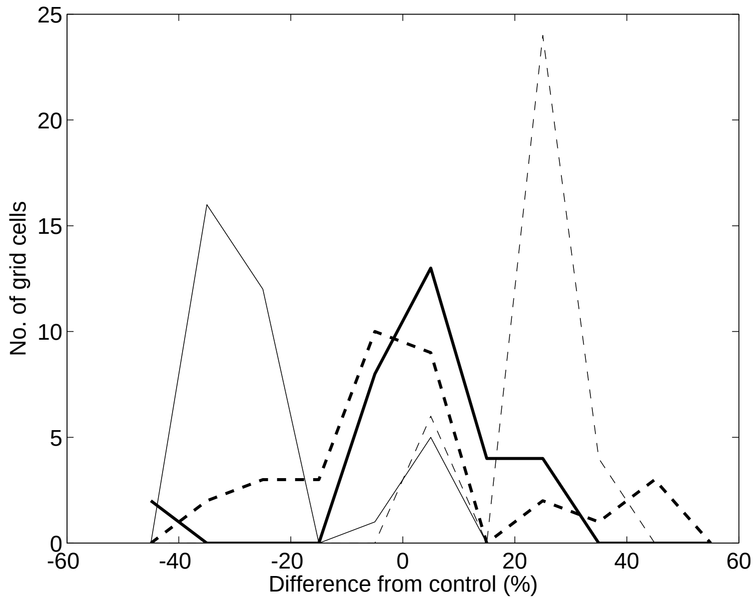
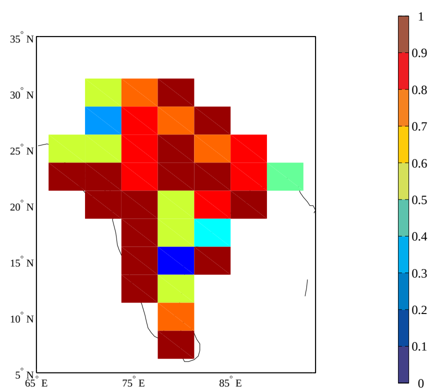
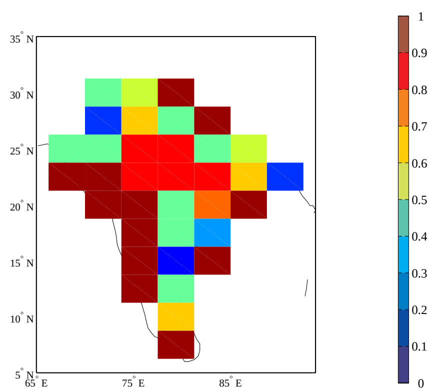


Figure 3: Histogram of the percentage difference in mean yield between the control present day simulation (C) and four present day yield simulations. Two simulations (thin lines) are for perturbed transpiration efficiency. The remaining two simulations are for perturbed climate: the thick solid line is $\lambda1$ and the thick dashed line is $\lambda2$.

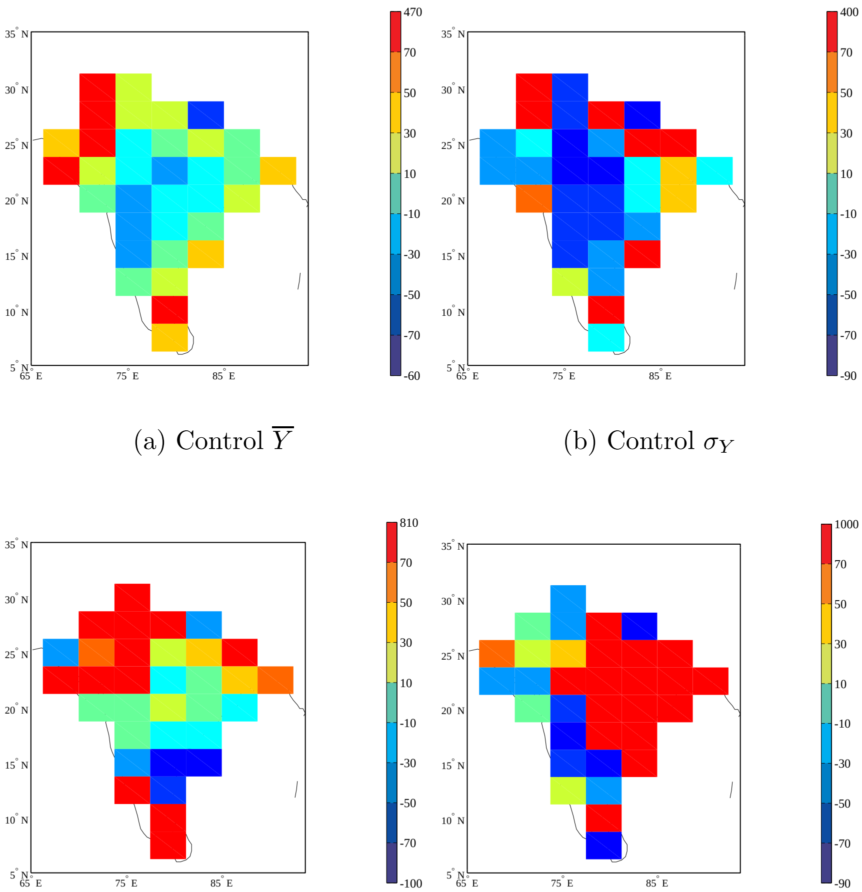


(a) TOL



(b) SEN

Figure 4: The twenty–year mean of the percentage of setting pods for the two simulated heat tolerance characterstics, tolerant and sensitive, in the doubled CO_2 $\lambda3$ simulations.



(a) Control $\overline{Y}$

(b) Control σ_Y

(c) $\lambda 3$ $\overline{Y}$

(d) $\lambda 3$ σ_Y

Figure 5: Percentage changes in the statistics of yield between the present–day control simulation and doubled CO_2 climates for two of the parameter pertubations.