# Climatic Change

## Towards a genotypic adaptation strategy for Indian groundnut cultivation using an ensemble of crop simulations

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## Abstract

Climate change has been projected to significantly affect agricultural productivity and hence food availability in the coming decades. The uncertainty associated with projecting climate change impacts is a barrier to agricultural adaptation. Despite uncertainty quantification becoming more prominent in impact studies, the thorough quantification of more than one uncertainty source is not commonly exercised. This work focuses on Indian groundnut and uses the General Large Area Model for annual crops (GLAM) to investigate the response of groundnut under future climate scenarios, develop a genotypic adaptation strategy, and quantify the main uncertainty sources. Results suggest that despite large uncertainty in yield projections (to which crop- and climate-related sources contribute 46 and 54 %, respectively) no-regret strategies are possible for Indian groundnut. Benefits from genotypic adaptation were robust towards the choice of climate model, crop model parameters and bias-correction methods. Groundnut breeding for 2030 climates should be oriented toward increasing maximum photosynthetic rates, total assimilate partitioned to seeds, and, where enough soil moisture is available, also maximum transpiration rates. No benefit from enhanced heat stress tolerance was observed, though this trait may become important as warming intensifies. Managing yield variability remains a challenge for groundnut, suggesting that an integral approach to crop adaptation that includes year-to-year coping strategies as well as improvements in crop management is needed across all India.

## 1. Introduction

Climate change has been projected to significantly affect agricultural productivity and hence food availability in the coming decades, with particularly negative effects across the global tropics (Challinor et al. 2014). Model-based projections of climate change impacts on crop productivity are critical for understanding cropping system responses under climate change scenarios so as to plan adaptation. However, such projections are subjected to numerous uncertainties which in cases can hinder adaptation planning (Vermeulen et al. 2013). Major knowledge gaps and uncertainties associated to crop responses in future scenarios remain (e.g. which processes are key to simulate future yields, how predictable these are, how do biophysical drivers interact with the broader socio-economic and cultural context in farming systems). A better understanding of impacts and their associated uncertainties will aid agricultural adaptation to climate change.

Here, we aim at assessing climate change impacts and genotypic adaptation for the groundnut crop in India. Originating in South America, groundnut is a grain legume widely grown across India. Groundnut is produced mainly as a cash crop, with roughly 82 % of groundnut production used for edible oil, 12 % as seed, and 6 % as feed (Mehrotra 2011). India is the second largest producer (~8.3 million tonnes in 2010) after China, and has the largest harvested area globally (~5.86 million hectares in 2010). Average Indian groundnut crop yields of 1.4 ton ha$^{-1}$, however, are low (17 % below worldwide average in 2010) (Mehrotra 2011; FAO 2014). With respect to non-water-limited yields (~5,500 kg ha$^{-1}$ on average), actual yields are also low (1,020 kg ha$^{-1}$ on average) (Bhatia et al. 2009). Low yields are the consequence of interannual variations in monsoon precipitation and a cropping system that is highly sensitive to interannual climate variability (Singh et al. 2012). Under climate change scenarios of increased temperatures and changing patterns of precipitation, Singh et al. (2012) projected decreases in groundnut crop yields from 6 to 44 % across different regions of India by 2050, and Challinor *et al*. (2007) projected yield decreases of up to 70 % for rainfed groundnut areas by 2100. Genotypic modifications, which involve the incorporation of desirable traits aimed at tolerating stresses to achieve greater and more stable yields, and more broadly the design of crop “ideotypes” (i.e. varieties with ideal genetic characteristics), have been suggested as a key strategy for Indian groundnut systems (Challinor et al. 2009; Singh et al. 2013).

An assessment of near-term climate change impacts on groundnut productivity, potential genotypic-level adaptation strategies that thoroughly quantifies uncertainty and robustness in model projections has not been carried out to date. Characterising the sources of uncertainties is key in order to improve modelling frameworks and make more informed decisions (Vermeulen et al. 2013). Additionally, by focusing on the 2030s period the analyses presented here are also more likely to be of use to the breeding community in early breeding cycles during the 21st century. The objectives of this paper were to:

(1) Assess the potential benefit from crop improvement by quantifying changes in mean and interannual variability of crop yields in hypothetical crop improvement scenarios with respect to no-adaptation scenarios (Sect. 3.1).
(2) Investigate robustness of future yield projections and quantify the relative importance of crop- and climate-related modelling uncertainties (Sect. 3.2).

The analyses performed herein contribute to improve understanding of the processes driving crop responses under future scenarios, to quantify the relative importance of crop and climate model uncertainties in regional impacts estimates, and to assess the effectiveness of the potential genotypic adaptation options in addressing climate change.

## 2. Materials and methods

The study areas were all 1 x 1º grid cells (a total of 195) of India where groundnut is reportedly cultivated (Figure 1) (Challinor et al. 2004). The study region was divided in five growing zones (Figure 1A), which reflect the variation in the germplasm grown in India (Mehrotra 2011). An ensemble of simulations based on GLAM (General Large Area Model for annual crops, Sect. 2.3.1) (Challinor et al. 2004) and the CMIP5 climate model ensemble (Taylor et al. 2012) was used to simulate growth and development of the groundnut crop in India under present-day and future (2030s, RCP 4.5) conditions using region-specific parameter ensembles calibrated against observed crop (Sect. 2.2.1, Figure 1B,C) and weather data. Ensemble simulations were then used to evaluate potential crop improvement scenarios and quantify potential gains in mean crop yield and yield variability (Sect. 2.3.4).

### 2.1. Input data

#### 2.1.1. Crop and soil data

District-level time series of groundnut area harvested, total production, crop yields and irrigated area for the period 1966–1993 were obtained from a previous study (Challinor et al. 2004), and then scaled onto a 1x1º resolution (ca. 100 x 100 km at the Equator) grid [see Sect. 2.2.2 and Ramirez-Villegas et al. (2015)]. A total of 195 grid cells were included in the analyses. The planting windows from the global study of Sacks et al (2010) were downloaded, aggregated onto the analysis grid (1x1º) and checked for inconsistencies to ensure planting windows reflected monsoon dynamics (Ramirez-Villegas et al. 2015). Spatially variable soil hydrological parameters, namely, permanent wilting point ($\theta_{ll}$), field capacity ($\theta_{ul}$), and saturation ($\theta_{sat}$) were derived from the 30 arc-sec Harmonized World

Soil Database (HWSD) (Batjes 2009). Crop model simulations in each grid cell were always associated with their respective soil moisture limits ($\theta_{ll}$, $\theta_{ul}$, $\theta_{sat}$).

### 2.1.2. Climate data

Historical observation-based daily precipitation data were gathered from the Centre for Climate Change Research (CCCR) of the Indian Institute for Tropical Meteorology (IITM) (available at http://cccr.tropmet.res.in/home/index.jsp, accessed Sept 2011) at a spatial resolution of 1x1° and for the period 1961–2008 (Rajeevan et al. 2006). This interpolated dataset is the only observed precipitation dataset that covers the entire analysis domain at a daily time step required for GLAM for the period for which yield observations were available. Daily maximum and minimum temperatures were gathered from a previous GLAM study in which monthly interpolated data from the Climatic Research Unit (CRU) dataset (available at https://crudata.uea.ac.uk/cru/data/hrg/, accessed 1st September 2011) were linearly scaled to daily values (Challinor et al. 2004), whereas daily downwards shortwave solar radiation data were gathered from the European Centre for Medium-Range Weather Forecasts (ECMWF) 40+ Reanalysis (ERA-40) (Uppala et al. 2005). ERA-40 was used as it provided a realistic representation of daily solar radiation and its variability (Uppala et al. 2005). Historical data were used for (1) bias correcting the climate model simulations from the CMIP5 ensemble (see below), and (2) calibrating the crop model (Sect. 2.2.2).

Daily CMIP5 outputs of historical and RCP4.5 transient simulations were downloaded from the CMIP5 archive, freely available at http://pcmdi9.llnl.gov/esgf-web-fe/ (Taylor et al. 2012). Data for a total of 13 GCMs for both historical (“baseline”, 1966–1993) and future (2022-2049 “2030s”) periods were gathered (Table S2). Simulated GCM outputs were first bias corrected before being used into the crop model, so as to reduce the impact of climate model bias on crop simulation (Ramirez-Villegas et al. 2013). Since the uncertainty associated with the choice of bias correction (BC) method is usually not quantified in impact studies, three different methods were used in order to quantify uncertainty from this process, as follows:

- Simple bias correction (SH): The SH method, also referred to as nudging, used the difference between the observed and GCM simulated climatological means in the historical period to correct the future daily GCM output (Hawkins et al. 2013). This process was done for each grid cell, variable, month and GCM simulation (i.e. correction factors varied spatially, seasonally, and across GCMs and variables). For temperature (maximum and minimum), arithmetic differences were used, whereas for precipitation and solar radiation relative differences were used.
- Change factor (DEL): The DEL method, also referred to as the delta method (Ver Hoef 2012), consisted of first calculating the difference between the projected and the historical GCM values (the delta) for each grid cell, month and variable and then adding such delta to the historical observations to obtain daily climate data for future conditions (Hawkins et al. 2013). This method is amongst the most frequently methods for bias-correction in the climate change impacts literature [e.g. Asseng et al. (2013); Koehler et al. (2013)].
- Local intensity scaling (LOCI): This technique consists in correcting both wet-day intensity and frequency, while leaving solar radiation and temperatures uncorrected (Themeßl et al. 2011). On a monthly basis, two parameters were estimated: the model

wet-day threshold and the scaling factor. The model wet-day threshold was estimated as the threshold above which the number of wet days predicted by the model equalled the number of wet days in the observations (of 1 mm day$^{-1}$). Next, the scaling factor is estimated as the ratio of climatological mean of wet days in the observations to that of the GCM subtracted from their respective wet-day thresholds. The monthly correction factor and the wet-day threshold are then used to correct the intensity and frequency in both the historical and the future GCM simulations. For more details and underlying equations the reader is referred to Themeßl et al. (2011).

All methods were applied for each GCM at a resolution of 1x1º. The resulting datasets were all at daily scale for the periods 1966-1993 (historical) and 2022-2049 (RCP4.5). For a more complete description and analysis of these methods and a review of other methods the reader is referred to Hawkins *et al*. (2013) and to Themeßl *et al*. (2011).

## 2.2. Modelling approach

### 2.2.1. Crop model

In this study, the General Large Area Model for annual crops (GLAM) (Challinor et al. 2004) was used to perform all crop simulations. In GLAM, crop development is divided into five phases: sowing to emergence (R0), emergence to flowering (R1), flowering to start of grain filling (R2), start of grain filling to maximum leaf area index (R3), and maximum leaf area index to physiological maturity (R4). Total crop biomass is estimated on a daily basis using the product of the total plant transpiration and the transpiration efficiency ($E_T$), whereas grain yield is estimated using the total biomass and the time-integrated rate of change in the harvest index ($\partial H_I/\partial t$). Leaf area growth in GLAM is simulated using a prescribed constant leaf area index (LAI) growth rate ($\partial L/\partial t$). Additionally, the yield gap parameter ($C_{YG}$) is a model constant that accounts for non-modelled processes that reduce crop yields (such as sub-optimal management and pests and diseases). Four different parameterisations of $CO_2$ response in order to quantify uncertainty from this process, consistent with a C3 physiology and described by Challinor and Wheeler (2008), were used to simulate the response of groundnut to increased $CO_2$ concentrations. More details on $CO_2$ response are presented in SI Text 1 and Table S1.

### 2.2.2. Crop model calibration and baseline simulations

Due to lack of observational constraints to calibrate each of the parameters (i.e. only yield data was available), a parameter ensemble approach was adopted as described in SI Text 2. Once the crop model was calibrated, three sets historical of simulations were conducted in which the only difference was the meteorological inputs: LOCI, SH and DEL. In all cases, calibration of $C_{YG}$ was done iteratively for each GCM and bias correction method weather input. Each set of baseline simulations consisted of 195 grid cells, 19 parameter ensemble members and 13 GCMs for the full 28-year baseline period 1966-1993.

### 2.2.3. Future crop simulations

Firstly, three sets of future yield no-adaptation simulations were carried out (LOCI, DEL, SH) each consisting of 13 GCMs, 19 parameter ensemble members, the 4 $CO_2$ parameterisations, and 195 grid cells (i.e. a total of 988 simulations per grid cell and bias correction method). These simulations were used to assess the impact of future climates on groundnut yields by computing the percentage change in yield from the baseline.

Next, genotypic simulations were performed. The first step in designing genotypic adaptation simulations was the identification and mapping of traits onto the GLAM parameter space, i.e. associating the different traits and their observed distributions (or ranges) to specific parameters and their calibrated values. Supplementary Table S3 shows the main studies that have investigated genotypic improvement of groundnut using crop models. The different studies highlight the importance of five genotypic properties, namely, maximum photosynthetic rate, partitioning to seeds, leaf thickness and size, crop development rate, and temperature tolerance. These traits are listed and matched to appropriate GLAM parameters in Table 1.

[Table 1 here]

The second step was then the design of hypothetical crop improvement scenarios. Crop improvement scenarios were designed by perturbing each of the parameters in Table 1 from their calibrated value up to a global upper value derived from the literature. Maximum values used were large enough so as to include potential from available germplasm in other parts of the world. Establishing a new maximum value for as many parameters as possible was preferred instead of using fixed percentages for all parameters [e.g. Singh et al. (2012)], since it provides a more realistic estimate of genotypic adaptation limits (Challinor et al. 2009). Parameter perturbations were in all cases, except for those associated with thermal durations ($t_{TT0}$, $t_{TT1}$, $t_{TT2}$, $t_{TT3}$, see footnote in Table 1 for their meaning), done via increases of 25 %, 50 % and 100 % of the absolute difference between the calibrated parameter value and the global upper value (Table 1). Each parameter was first perturbed in isolation (i.e. 14 parameter x 3 perturbations = 42 individual perturbations). Next, two combined parameter scenarios were constructed; scenario 1: lowest perturbation of each parameter and increased $t_{TT0}$; and scenario 2: lowest perturbation of each parameter and decreased $t_{TT0}$. The total number of perturbations was thus 44: 42 (individual), plus 2 (combined). The GLAM model was used to simulate crop yield for the 44 genotypic adaptations applied to the 19 baseline parameter sets, in each of the 195 grid cells for the 4 $CO_2$ parameterisations, 13 GCMs and the 3 bias-correction methods, i.e. a total of 44 x 19 x 195 x 4 x 13 x 3 simulations.

### 2.3. Data analysis

All simulations herein analysed were carried out with the model GLAM. Analyses focus on two elements of food security: availability through the calculation of mean yield and stability by computing yield coefficient of variation (*CV*).

#### 2.3.1. Quantification of climate change impacts and the benefits of genotypic adaptation

Model output was first verified for consistency using maximum values reported in the literature for three key variables: (a) crop yield, (b) crop duration, and (c) end of season harvest index. Simulations with time-mean yields larger than 6,500 kg ha$^{-1}$ (Balota et al. 2012), mean duration greater than 150 days (Nigam 2009; Singh et al. 2012), or harvest index greater than 0.66 (Nigam et al. 2001) were considered unrealistic and hence rejected.

Changes in crop yield mean and variability under no adaptation were quantified as percentage deviation from the baseline (see SI Text 3), whereas changes in crop yield mean and variability for genotypic adaptation simulations were quantified by first calculating the percentage deviation from the baseline and then the difference from the no-adaptation runs. Based on literature review (see Supplementary Table S3), the effects of crop improvement scenarios were analysed by grouping parameters according to the main abiotic stress being addressed as follows:

- *Drought management*: drought escape through reduced thermal time requirement during vegetative phase ($t_{TT0}$), increased water-use efficiency through increases in transpiration efficiency ($T_E$, $E_{TN,max}$), harvest index ($\partial H_I/\partial t$), maximum transpiration rate ($TT_{max}$) and specific leaf area ($SLA_{max}$).
- *Increased duration*: enhance LAI growth, light interception and biomass accumulation through increases in all thermal time requirements ($t_{TT0}$, $t_{TT1}$, $t_{TT2}$, $t_{TT3}$, see footnote in Table 1 for meaning of parameters).
- *Temperature extremes adaptation*: increase tolerance to high temperature during flowering ($T_{crit}$, $T_{lim}$, $T_{ia}$), and improved photosynthesis response to temperature ($T_{ter1}$).

These groups are hereafter used to present and discuss the results.

### 2.3.2. Quantification of robustness in model projections and uncertainty decomposition

We assessed robustness, i.e. how large is the mean signal of change in comparison to the uncertainty, in model simulations by calculating a robustness index ($R$) after Knutti and Sedlacek (2012). This quantity considers the magnitude of the change, the sign, natural variability and inter-model spread, and is defined as $R=1-A_1/A_2$, where $A_1$ is the uncertainty: the area between two cumulative density functions (CDFs) characterising the individual model projections and the ensemble mean projection; and $A_2$ is the signal: the area between two CDFs characterising the ensemble mean projection and the historical simulation. A value of $R$ equal to 1 implies that the cumulative density functions of ensemble members are equal to that of the ensemble mean –perfect model agreement. Values of $R < 0.5$ reflect little agreement between model projections, whereas values above 0.8 reflect significant agreement in model projections (Knutti and Sedláček 2012).

We define uncertainty as the range (i.e. difference between the maximum and minimum value) of a model prognostic variable (i.e. yield) among many model configurations for a given grid cell. Here, the total future uncertainty in mean yield was calculated as the sum of four sources following Koehler *et al* (2013): (1) GLAM parameter sets, (2) GCMs, (3) BC and (4) $CO_2$ parameterisation. For each source, the fractional uncertainty ($F_U$) was calculated as the ratio of uncertainty of a given source to the total uncertainty.

## 3. Results

### 3.1. Potential benefits from genotypic adaptation

Because the focus of this paper is on genotypic adaptation gains, all results and discussion below focus primarily on genotypic adaptation simulations (at +50 % increases, unless otherwise stated) and their difference with respect to no-adaptation simulations. For a comparison of no-adaptation simulations and baseline simulations the reader is referred to SI Text 3.

#### 3.1.1. Gains from drought management

Figure 2 shows the potential mean yield gains from improving drought-related traits for DEL simulations (for figures of LOCI and SH simulations see Supplementary Fig. S7). Improving partitioning to seeds ($\partial H_I/\partial t$) was overall the most geographically consistent trait in its impact. Mean yield gains of 20-40 % were observed in southern India, of 40-60 % in central, eastern and western India, and of up to 80 % in northern India. Improving photosynthetic rates as implemented in GLAM (i.e. parameters $T_E$, $E_{TN, max}$) proved to be less effective than improving partitioning; however, significant gains in southern and northern areas were achieved from improving this trait. The impact of enhanced maximum transpiration rate ($T_{Tmax}$) was large in northern and eastern India (generally above 60 %), but was less significant in the drier areas of the west and the warmer areas of the south. Improving leaf thickness through changes in $SLA_{max}$ and reducing the duration of the vegetative stage ($t_{TT0}$) produced negligible changes in mean yield. Changes in yield variability were mostly negative or negligible, indicating that achieving temporal yield stability is a more challenging task than improving mean yield (Figure 3, Supplementary Figure S8). Overall, improving photosynthetic rates ($E_{TN, max}$, $T_E$) produced the greatest improvements in yield stability.

[Figure 2 here]

### 3.1.2. Gains from increased duration

Increased duration of the grain filling to physiological maturity phase ($t_{TT3}$) was the most effective phenology trait. In eastern India, mean yield gains from this trait were in the range 12 – 15 % for a 10 % increase in $t_{TT3}$, whereas changes were lower in southern and western India (8 – 10 %). The effectiveness of $t_{TT3}$ was followed by that of the duration from the start of pod filling to maximum LAI ($t_{TT2}$), indicating that substantial yield gains would be achieved if both were increased simultaneously (i.e. overall increasing the grain filling period). A longer vegetative period ($t_{TT0}$) was less effective, with yield gains generally below 10 % (compared to 8 – 15 % for $t_{TT2}$ and $t_{TT3}$). The least effective trait was the duration of the flowering stage ($t_{TT1}$), with mean yield changes generally below 6 % (Figure 3, Supplementary Figure S9). Improvements in yield stability were found in most of India for $t_{TT0}$ and $t_{TT1}$. Yield *CV* decreased by 5-15 % in the east –where monsoon precipitation is higher (Supplementary Figure S10).

**3.1.3. Gains from temperature extremes adaptation and breeding of multiple traits**

GLAM simulates the impact of heat stress by reducing pod-set percentages if high temperature events of sufficient length occur during the flowering period. Yield mean and variability changes from improved heat stress were negligible across the whole country (mean change < 1 % for both mean and *CV*, Fig. 3). The lack of effect of temperature extremes on crop productivity may highlight the fact that a first breeding cycle (to target cultivar release by 2030) should not focus on improved heat tolerance.

In general, combining traits boosted crop yields across the whole study area (scenarios $t_{TT0\_i}$ and $t_{TT0\_d}$, Figure 3, Supplementary Figure S11). In many areas, crop yield gains exceeded 100 % relative to the future climate scenario projected mean yield. Thus, there is large potential from breeding the right combinations physiological traits into existing germplasm. Interannual yield variability, conversely, showed a relatively inconsistent response both across the geographic space and across these two genotypic adaptation scenarios ($t_{TT0\_i}$ and $t_{TT0\_d}$). Yield stability declined across most of the territory, with increases in *CV* beyond 15 % in many areas of India (Supplementary Figure S12).

### 3.1.4. Compared trait effectiveness

The relative effectiveness of the different traits and trait groups varied significantly for both yield means and yield variability (Figure 3). There were greater mean yield gains from virtually all drought-related traits as compared with longer duration traits (Figure 3A, C). More specifically, improving the partitioning to seeds had a greater impact than all other individual traits, as it boosted mean yields above 50 % in ~50 % of the grid cells. This suggests that partitioning to seeds should be a high priority trait in any breeding effort now so as to develop resilient germplasm that can be tested sufficiently early so as to be prepared for 2030 climates. Harvest index breeding has been well-studied and is already a priority in the breeding of groundnut and other crops (Donald and Hamblin 1976; Nigam 2009). For rainfed yield variability (Figure 3B, D), it is important to note that more stability was only achieved through: (1) increases in photosynthetic rates ($T_E$, $E_{TN, max}$), (2) improved effective LAI ($SLA_{max}$, increased $t_{TT0}$), and (3) increases in the length of the early vegetative and flowering period ($t_{TT0}$ and $t_{TT1}$). This highlights the need to understand and manage year-to-year yield responses through crop management (e.g. shifts in sowing dates, supplementary irrigation).

[Figure 3 here]

### 3.2. Robustness and uncertainty sources in genotypic adaptation options

Robustness in adaptation simulations was high in central, western and eastern India (Figure 4A, B). Robustness was lower when all ensemble members were considered individually (i.e. 2 BC methods x 13 GCMs x 4 $CO_2$ response parameterisations x 19 parameter sets =

1976 simulations), with mean value of 0.47, and 14.8 % of the area with R>0.8 [see methods and Knutti and Sedlacek. (2012)]. When results were pooled by uncertainty source, however, some 70 % of India presented R > 0.8 (Supplementary Figure S13). This suggested that interactions between individual choices may be a significant source of uncertainty.

Uncertainty decomposition indicated that climate was the largest source of uncertainty (Figure 4C), with a mean contribution of 54 %. Geographic differences were found in the relative contribution of different sources to total yield uncertainty, with north-western India more dominated by climate uncertainty and south-eastern India more dominated by crop uncertainty. The most important climate source of uncertainty was GCM structure with a mean contribution to total yield uncertainty of 36 % (Supplementary Figure S14). GLAM parameters were the most important crop model source of uncertainty (mean = 39.4 % from total yield uncertainty).

## 4. Discussion and conclusions

### 4.1. Importance of traits and underlying processes

Indian groundnut production is highly sensitive to interannual climate variability, sub-seasonal weather variations, and climate change (Bhatia et al. 2009; Challinor et al. 2009; Mehrotra 2011). This study shows that increasing yield potentials through genotypic improvement is a very effective climate change adaptation measure. Simulations of adaptation showed gains (albeit sometimes small) in mean crop yields across virtually all the different simulated traits across the study area, except for the reduction in the vegetative stage duration ($t_{TT0}$). This result seems robust and was in agreement with previous studies where yield gains were reported either by enhancing crop duration or by improving crop growth traits (Challinor et al. 2009; Singh et al. 2012; Singh et al. 2013). In particular, it must be noted that the mean yield gains reported here were much less spatially variable than those of Singh et al (2012). Such differences may be attributed to the fact that Singh et al (2012) assessed only a handful of sites, a different period (2050), and they used a different crop model (CROPGRO). Here, the most effective set of traits for improving mean yields were those related to improved drought management (Figure 3), and in particular a better partitioning to the seeds (Figure 2). In this regard, previous work reported that increased partitioning to seed presented a more spatially consistent and stronger response than an increase in the photosynthetic rate –as was found here (Singh et al. 2012; Singh et al. 2013). Better assimilate allocated to the seeds has been pointed out as one of the most important traits for achieving greater yields (Nigam and Aruna 2008; Nigam 2009). The harvest index is also a trait that shows large variation within the groundnut genepool and is easy to select for in agronomic trials (Rao and Nigam 2003), and thus the opportunities of breeding higher partitioning are substantial.

The results presented here indicate that, as stressed by other authors [e.g. Nigam (2009)], gains from improvements in the transpiration rate are limited to areas with limited or no water stress during the growing season –though this trait negatively impacted yield stability. This was clearly evidenced since the dry areas of Gujarat (western India, Z1 in Fig. 1) and of the south (primarily Andhra Pradesh, Z5 in Fig. 1) showed little yield gains from improving this trait (Figure 2). In these environments, however, yield gains could be achieved through greater photosynthetic rates [herein parameterised as higher $T_E$ or $E_{TN,\,max}$, also see Nigam (2009)].

Food security comprises four dimensions: availability, access, utilisation, and stability. The temporal stability of yield is not often assessed in climate change studies (Challinor et al. 2014). Farming communities require stable harvests so as to be able to maintain and, where possible, increase the flow of produce to national and international markets. Because changes in the temporal variability of crop yields can increase vulnerability locally and regionally, adaptation to climatic extremes is needed. In this study, the most effective traits in increasing mean yields also caused increased vulnerability to extremes (i.e. larger yield *CV*). These included the harvest index (most effective individual trait for mean yields), the maximum transpiration rate, and the increases in duration of grain filling ($t_{TT2} + t_{TT3}$). Mechanisms for these results can be inferred in some cases. In the case of the harvest index, for instance, yield decreases were concentrated in dry areas. This suggested that while in wet years increased harvest index allowed attaining higher yields, in very dry years a higher $\partial H_I/\partial t$ may trigger terminal drought earlier than normal (Challinor et al. 2009). Similarly, a longer reproductive period may expose the crops to terminal drought in very dry years. $T_{Tmax}$ caused the greatest yield stability reduction, probably via increased water stress in dry years. Since there was no single 'silver-bullet' trait that increased both mean yield and yield stability everywhere, results suggested that (1) yield means and yield stability may be achieved through different traits; and (2) it is critical for farmers in the field to cope with short-term variations through improved agronomy. We thus argue that an integral approach to crop adaptation is needed.

### 4.2. Crop breeding under uncertainty

Decisions on how and where to adapt a given cropping system cannot be delayed until outcomes are predicted with absolute certainty. Work on uncertainty quantification remains incipient in many aspects of crop modelling. Existing studies limit the quantification of modelling uncertainty to either using multiple GCMs with a single crop model, to the use of crop model parameter ensembles with a single bias-corrected set of GCM simulations (Tao et al. 2009), or to the use of multiple crop models with a single bias-corrected set of GCM simulations (Asseng et al. 2013). We demonstrated that, contrary to what has been hypothesised earlier [e.g. Rotter (2014)], despite uncertainty, no-regret strategies are possible [also see Ramirez-Villegas et al. (2015)]. Uncertainty in actual values of yield was large, with almost equal contributions from climate and crop uncertainty (54 % and 46 %, respectively), but in no case these uncertainties precluded a consistent and coherent simulation of genotypic adaptation. The direction of yield changes between no-adaptation and adaptation simulations was consistent across simulations, with robust ($R > 0.8$) results for the majority (~70 %) of the study area in all modelling choices (BC method, GCM, GLAM parameters, and $CO_2$ response).

The findings of this paper thus suggest that a consistent picture of climate change adaptation for groundnut is possible through ensemble modelling. There was very high certainty that adaptation to climate change in groundnut cultivation is possible through increases in maximum photosynthetic rates, total assimilate partitioned to seeds, and, only in areas with sufficient soil moisture, also through increases in the maximum transpiration rate. It can also be said with high certainty that heat stress is not a major concern in the next 20-30 years for breeders, though varietal substitutions may be required at local levels as climate change intensifies (Challinor et al. 2007). Existing studies for other rainy season crops (e.g. soybean, rice) support the finding that heat stress is unlikely to be a current or near-term concern (Gourdji et al. 2013). We thus argue that the current focus of groundnut breeding is well on target, but that particular attention has to be paid to managing yield variability under future climate.

The main challenge here, however, remains to be the careful interpretation of modelling outcomes so as to provide information that is of use for breeders. Physiological crop models are limited to providing physiology-level conclusions. This information is often of limited use for breeders because it does not provide sufficient detail on the genetic background of the material that could be used for crop improvement, particularly for large-area models whose parameters are difficult to assimilate as real world genotypes. In this regard, a better mapping of traits on the model parameter space as well as coupling of physiological information and genomic information are topics that warrant future research.

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## Figure captions

**Figure 1** Study area divided into growing zones for model optimisation (A), observed mean 1966-1993 yield (in kg $ha^{-1}$) (B) and observed percentage coefficient of variation 1966-1993 (in percentage) (C). Zone notation as follows: NO: Northern; WE: Western; CE: Central; SE: South-Eastern; and PE: Peninsular. White areas are those where yield data was unavailable or where the proportion of area for peanut cultivation was below 0.2 %.

**Figure 2** Projected mean yield changes by 2030s as a result of crop improvement related to drought escape and water use efficiency. Shown are the ensemble mean results of delta bias-corrected simulations (DEL-corrected) for each of the genotypic properties. Associated model parameters are as follows: decrease in vegetative duration ($t_{TT0}$), increase in transpiration efficiency ($T_E$), increase in maximum transpiration efficiency ($\mathrm{E_{TNmax}}$), increase in rate of harvest index ($\partial H_I/\partial t$), increase in maximum transpiration rate ($T_{Tmax}$), and increase in specific leaf area ($SLA_{max}$).

**Figure 3** Comparative mean yield (A, C) and yield variability (as yield coefficient of variation, *CV*) (B, D) changes from different traits and trait groups. The spread shows the spatial variation in the response of each quantity (derived from means across simulations for each grid cell). Vertical black lines in panels A and B indicate different trait groups: drought management; increased duration, tolerance to temperature extremes, and all traits combined. Names of parameters are as follows: transpiration efficiency ($T_E$), maximum transpiration efficiency ($E_{TN,\ max}$), rate of change in harvest index ($\partial H_I/\partial t$), maximum transpiration rate ($T_{Tmax}$), maximum specific leaf area ($SLA_{max}$), thermal requirement for vegetative development ($t_{TT0}$), thermal requirement for flowering phase duration ($t_{TT1}$), thermal requirement for start of pod-filling to maximum canopy development ($t_{TT2}$), thermal requirement for maximum canopy development to physiological maturity ($t_{TT3}$), tolerance to heat stress at anthesis ($T_{crit}$, $T_{lim}$, $T_{ia}$), temperature at which transpiration efficiency starts to be reduced by heat stress ($T_{ter1}$), combined traits with decrease in $t_{TT0}$ ($t_{TT0\_d}$), combined traits with increase in $t_{TT0}$ ($t_{TT0\_i}$). In all panels, thick red horizontal line is the median, blue boxes mark the 25 and 75 % of the data and black whiskers extend to 5 and 95 % of the data.

**Figure 4** Robustness and uncertainties in model projections of adaptation. (A) robustness (dimensionless) calculated using the entire ensemble of model simulations (i.e. 1,976 ensemble members per grid cell); (B) robustness across ensemble member per modelling choice (2 members for BC method, 13 for GCM, 4 for $CO_2$ response, and 19 for GLAM parameters); (C) fractional contribution of climate and crop sources of uncertainty to total yield uncertainty. Thick horizontal red line is the median, blue boxes mark the 25 and 75 % of the data and black whiskers extend to 5 and 95 % of the data. See Figure S13 for mapping of individual sources of variation and Figure S14 for mapping of individual uncertainty sources.

**Table 1** List of genotypic properties and associated GLAM parameters

| Genotypic property | Parameter[1] | Max. value | Reference(s) |
|---|---|---|---|
| Max. growth rate | $T_E$ | 5.9 Pa | Brown and Byrd (1996)<br>Rao and Nigam (2003)<br>Jyostna Devi *et al*. (2009; 2010) |
| | $E_{TN, max}$ | 7 g kg$^{-1}$ | Brown and Byrd (1996)<br>Bhatnagar-Mathur *et al*. (2007)<br>Jyostna Devi *et al*. (2009) |
| | $T_{Tmax}$ | 0.7 cm day$^{-1}$ | Hammer *et al*. (1995)<br>Rao and Nigam (2003) |
| Partitioning to seeds | $\partial H_I/\partial t$ | 0.015 day$^{-1}$ | Hammer *et al*. (1995) |
| Leaf thickness and size | $SLA_{max}$ | 315 g cm$^{-2}$ | Phakamas *et al*. (2008)<br>Banterng *et al*. (2003)<br>Sheshshayee *et al*. (2006) |
| Crop development rate | $t_{TT0}$ | -20 % | N/A |
| | $t_{TT0}$ | + 20 % | N/A |
| | $t_{TT1}$ | + 20 % | N/A |
| | $t_{TT2}$ | + 20 % | N/A |
| | $t_{TT3}$ | + 20 % | N/A |
| Temperature tolerance | $T_{crit}$ | 38 ºC | Vara-Prasad *et al*. (2003)<br>Challinor *et al*. (2005) |
| | $T_{lim}$ | 38 ºC | Challinor *et al*. (2005) |
| | $T_{ia}$ | 44 ºC | Challinor *et al*. (2005) |
| | $T_{ter1}$ | 40 ºC | Challinor *et al*. (2005) |

[1]$T_E$: transpiration efficiency (Pa)
$E_{TN, max}$: maximum transpiration efficiency (g kg$^{-1}$)
$T_{Tmax}$: maximum rate of transpiration (cm day$^{-1}$)
$\partial H_I/\partial t$: rate of change in the harvest index (day$^{-1}$)
$SLA_{max}$: maximum possible value of specific leaf area (g cm$^{-2}$)
$t_{TT0}$: thermal requirement from planting to flowering (ºC day$^{-1}$)
$t_{TT1}$: thermal requirement from flowering to start of pod filling (ºC day$^{-1}$)
$t_{TT2}$: thermal requirement from start of pod filling to maximum LAI (ºC day$^{-1}$)
$t_{TT3}$: thermal requirement from maximum LAI to physiological maturity (ºC day$^{-1}$)
$T_{crit}$: maximum possible temperature at which grain-set starts to be affected by high temperature (ºC)
$T_{lim}$: maximum temperature at which grain-set is zero due to high temperature (ºC)
$T_{ia}$: temperature at which there is zero pod-set on the day of anthesis of a given flower due to a short duration high temperature event (ºC)
$T_{ter1}$: temperature at which transpiration efficiency starts to be reduced by heat stress (ºC)

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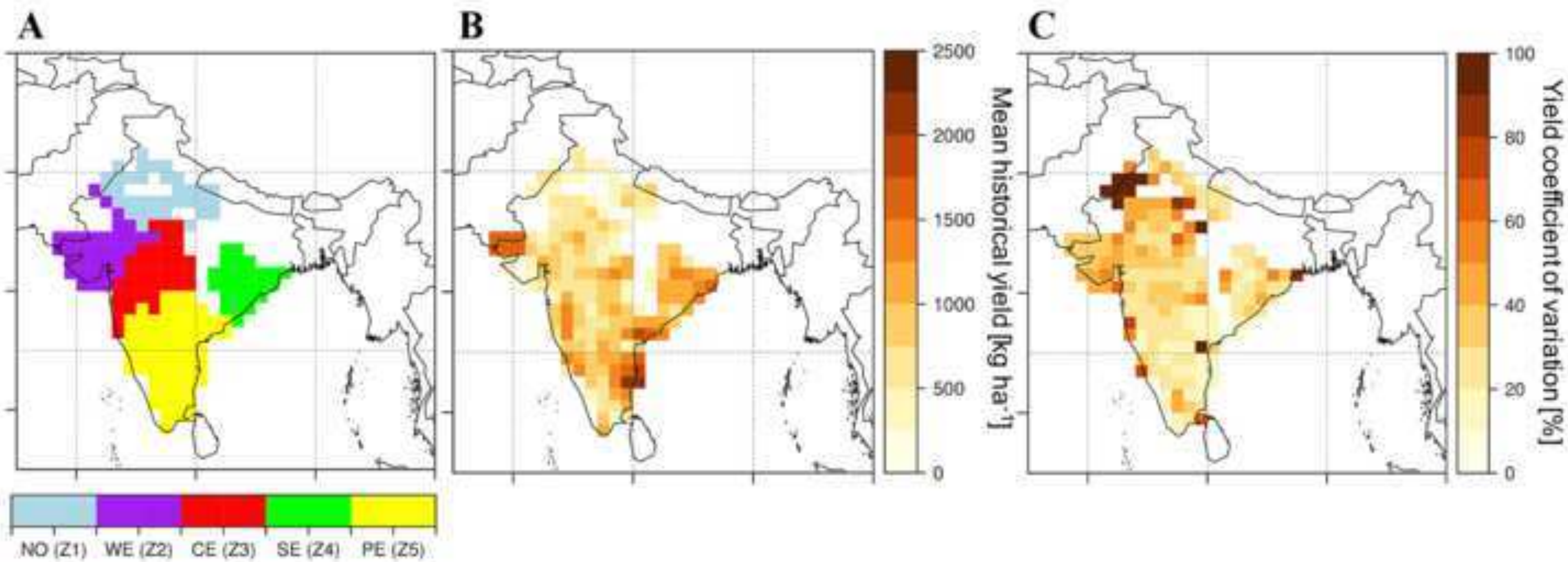

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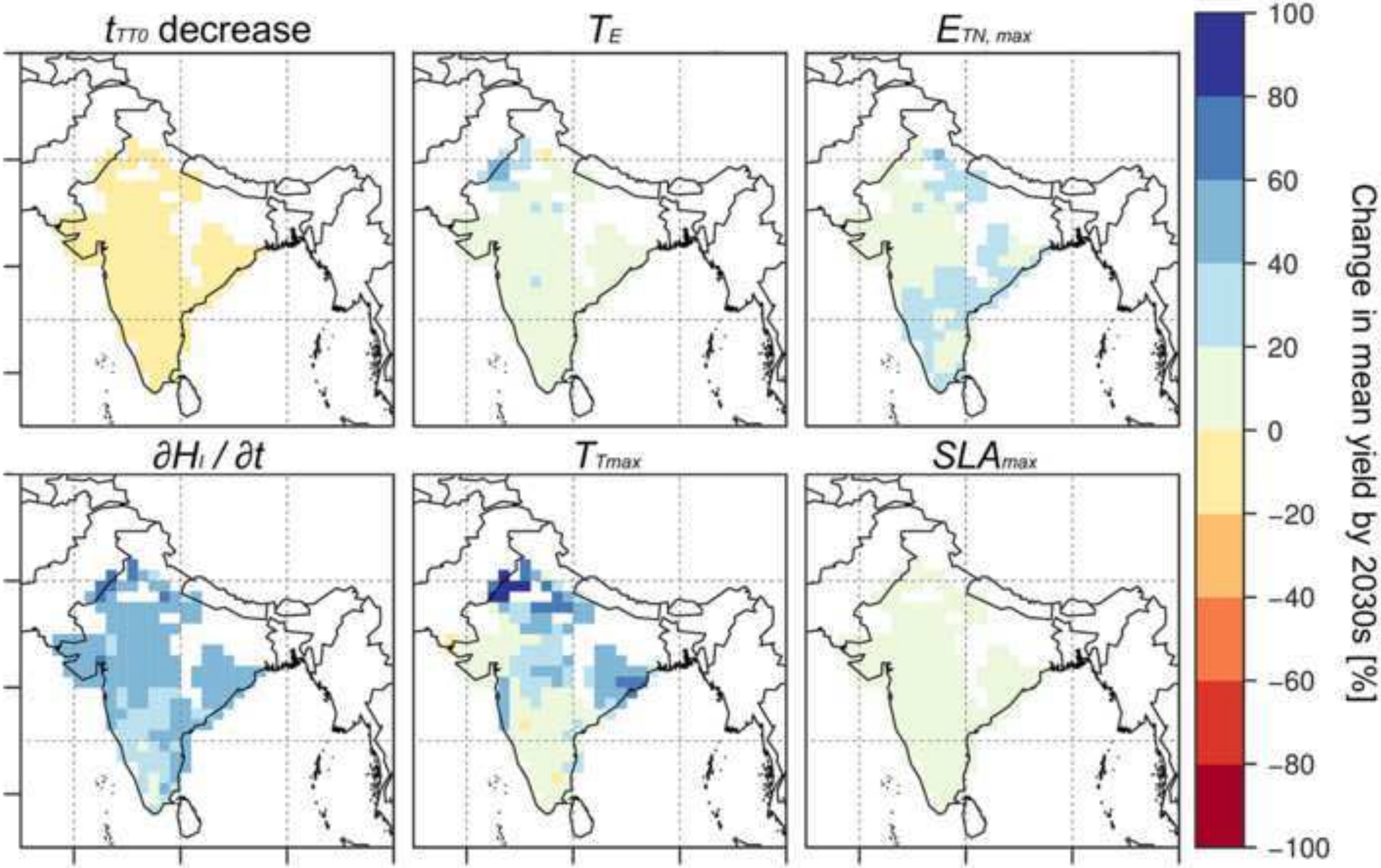

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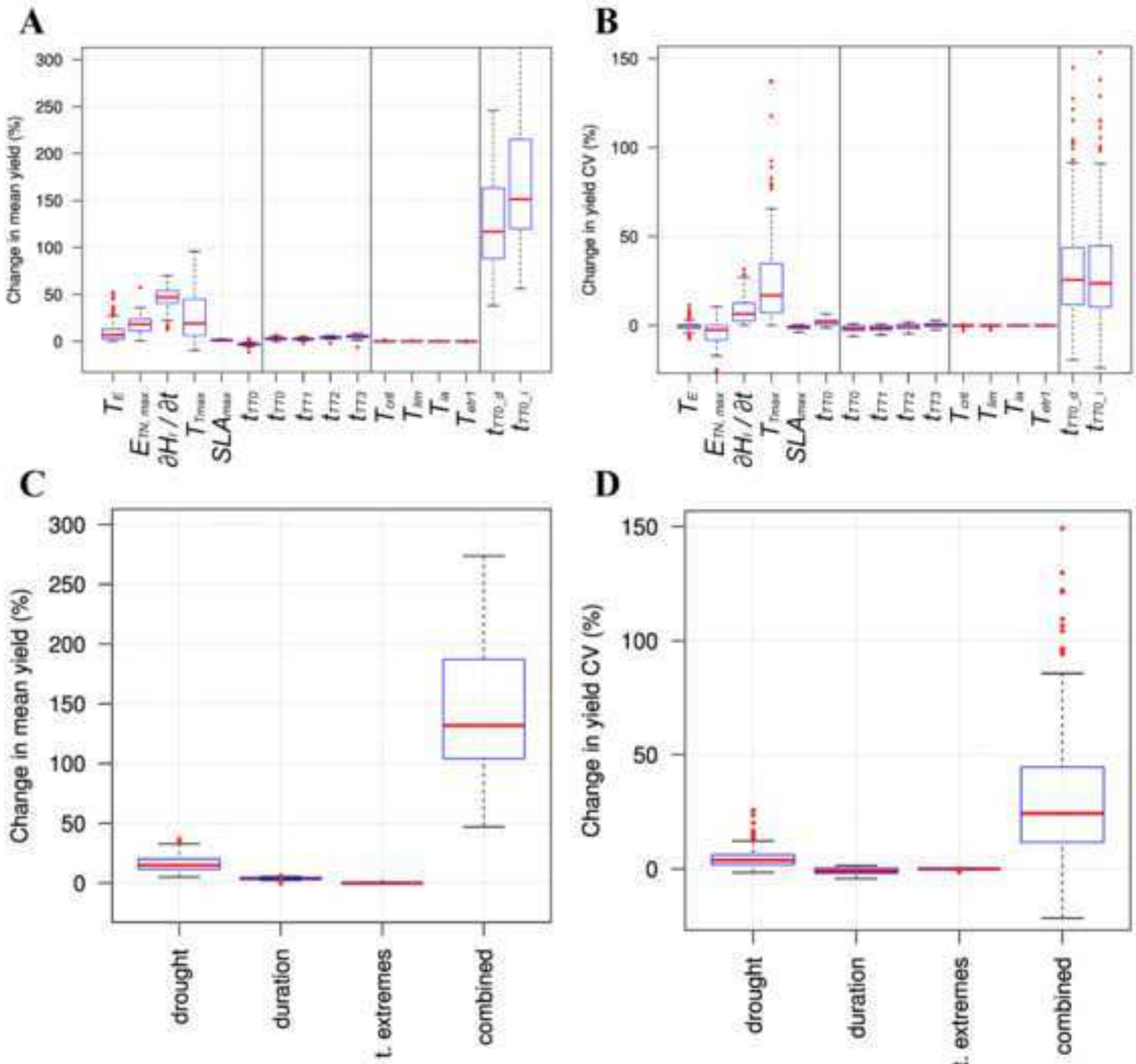

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