The impacts of climate change on Tamil Nadu rainfed maize production: a multi-model approach to identify sensitivities and uncertainties

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This study evaluates the impacts of climate change on maize yields in Tamil Nadu, and assesses the efficacy of adaptation strategies, using a novel multi-climate, multi-crop model approach based on AgMIP Protocols (www.agmip.org). While the climate models displayed consistent changes to rainfall and temperature, substantial uncertainty exists between the different climate-crop model responses that warrant further study. Adaptation strategies proved beneficial under a current climate context, but showed diminished efficacy under future climate conditions. We recommend that future work focus on identifying the main sources of climate-crop model uncertainty, and that additional work may focus on more transformative adaptation measures.

Keywords: Adaptation, climate change, crop model, climate model, maize.

Introduction

INDIA'S agricultural and economic well-being has historically been tied to the variability and strength of its monsoonal climate. In particular, the growing seasons in Tamil Nadu, India are dependent upon both the Southwest Monsoon (SWM) phase occurring between June–September, and the Northeast Monsoon (NEM) phase, which brings much of the annual rainfall between October–January and supplies nearly 42% of Tamil Nadu's agricultural production[1,2]. Both monsoonal phases depend on many factors and drivers of regional variability, such as: ENSO modulations, Indo-Pacific sea surface temperatures, Himalayan snowpack, and land surface changes[3]. Accurately simulating all components of the large–scale annual monsoon circulation has proven to be a difficult task for global climate models (GCMs), which show strong biases in the spatial and temporal distributions, the amount of monsoonal rainfall, the interannual variation in the strength of the monsoon heat lows, and the strength and geographic location of the major circulation features[4–6].

Generally, however, CMIP5 GCMs show increased mean temperatures across much of the world, even under less severe representative concentration pathways, and this finding extends over much of the Indian peninsula[7,8]. Other findings emerging from the Intergovernmental Panel on Climate Change Fifth Assessment Report indicate an intensification of the hydrological cycles such that 'wet' areas may receive more precipitation, a result salient to India's monsoonal climate, although the interannual and intra-seasonal variability of that rainfall is less certain[9]. Agricultural production must therefore be resilient to rising temperatures, and also to changing rainfall amounts, patterns, and variability[10]. Farmers may adopt various 'adaptation' management strategies that allow them to preserve their crops in the face of rising temperatures, or take advantage of increase in precipitation. Investments in adaptation options could prove significant, and so there is a need to better understand and characterize the nature of climate change impacts on regional crop yields, and how these vary across assessment tools and methods. Seasonal and sub-seasonal forecasts can aid farmers in adjusting their management practices on a short-term notice, but larger infrastructural projects require more time to plan and budget, and therefore characterizing the climate–agricultural regional impacts on longer timescales is also required. In order to consider what these adaptation strategies should be, stakeholders at multiple levels (e.g. district, state, federal etc.) require projections of crop response to potential future climate conditions, and a characterization of the uncertainty that surrounds these projections.

A multi-model intercomparison can serve these needs, and can provide a comprehensive assessment of crop response to climate change across the world and in the most vulnerable regions, creating a spatial analysis that

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can allow stakeholders to employ a range of strategies that are regionally tailored, but fulfill global objectives of building agro-ecosystem resiliency. The Agricultural Model Intercomparison and Improvement Project (AgMIP) (www.agmip.org) has created a set of protocols and methods to conduct regional integrated assessments (RIAs) of the impact of climate change on agriculture and farmer livelihoods. These RIAs comprised a climate and crop model intercomparison at a regional scale, with pilot projects being conducted in Sub-Saharan Africa and South Asia[11]. These protocols allow the RIA teams to assemble regional climate information for applications and identify sources of uncertainty; create future climate scenarios from a suite of CMIP5 GCMs, and compare the extent of climatic changes across these GCMs; utilize the climate change information in crop response simulations using multiple crop models; assess the general crop responses and uncertainty from these multi-model comparisons; and devise adaptation strategies to help stakeholders insulate themselves from losses due to climate change. The AgMIP protocols also extend to an agro-economic assessment in which the relative yield changes from the climate–crop intercomparisons are used to understand the socio-economic gains and losses across a distribution of farmers in targeted districts[2,12]. Tamil Nadu comprises part of the 'South India' AgMIP RIA, and the results shown here are preliminary assessments from this ongoing work. To focus on this study, we utilize and further develop the AgMIP climate-crop assessment protocols only to better understand the impact of climate change on rainfed maize yields in the Coimbatore District[11] (Figure 1). To do this, we study the following key questions:

- How do two crop models differ in their simulation of baseline maize yields across a heterogeneous distribution of farms and management?
- Using these two crop models, are there robust changes in crop yields across these farms due to projected mean climatic changes?
- What is the efficacy of various adaptation strategies under current climate conditions, and how does this change under future climatic conditions?

We also characterize some of the uncertainties in both the climate projections and crop response across the models used. This is among the first publications to discuss the preliminary findings and results of the AgMIP RIAs, which have, for the first time, coordinated an effort to study the impacts of climate change on agriculture using multiple climate and crop models[11]. To our knowledge, this is also among the first studies to utilize this multi-model approach to assess maize production in Tamil Nadu, and to present the uncertainties introduced by these models.

Next section details our methods: our selection of a subset of GCMs; our application of future climate change conditions; crop model information and calibration; and site selection. Our results for maize yields in the Coimbatore District, and includes our baseline climate–crop analysis; the application of various adaptation strategies under baseline conditions; the yield responses to future climate changes; and the application of the selected adaptation options under future climate conditions are presented later. Also we discuss the important findings and relationships identified for yields under baseline and future climate conditions, including the impacts and efficacy of the adaptation options tested. We also discuss sources of uncertainty and potential differences between the models, as well as limitations for identifying one model for use in climate–agriculture impacts assessments in this region. We conclude with a summary of findings and note the avenues for on-going and future work.

Methods and the AgMIP climate-crop protocols

Crop modelling methods and calibration

Agricultural scientists have extensively utilized process-based crop models as decision support tools to evaluate the impact of inter-annual climate variability and/or climate change on crop production[13–15]. Crop simulation models require high-quality data on local conditions, such as climate and weather, soil profiles, crop varieties and crop management details. Such data were obtained in the study region from different sources, inclusive of records from Tamil Nadu Agricultural University, administered farm household surveys, and the Department of Agriculture. The two crop models employed in this study

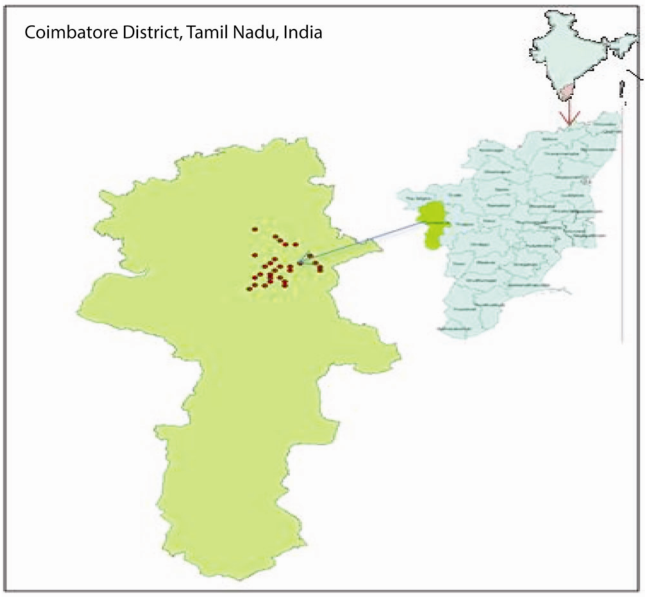

Figure 1. Map of AgMIP South India region, and the specific study district in Coimbatore, Tamil Nadu. The red dots indicate the approximate locations of the sampled farm households. Credited to Ponnusamy *et al.*[2].

were the Decision Support System for Agrotechnology Transfer CERES Maize[16,17] (DSSAT/CERES-Maize), and the Agricultural Production Systems Simulator (APSIM)[18]. These two models were used to simulate baseline (1980–2010) and future maize yield across a heterogeneous population of 60 farms across the Coimbatore district. Details on the simulation setup and calibration information can be found in Ponnusamy *et al.*[2] and are briefly described herein.

Crop management parameters used in the simulation set-up for individual farms were derived from the results of a pre-designed socio-economic survey, widely used within Tamil Nadu Agricultural University, and administered in our study region. The survey included a random selection of 60 representative farming households and information was collected for one year, while also querying about the farmers' experiences during 'normal' and 'extreme' periods. The survey was structured to capture details on the crop varieties used, planting dates, planting geometry, and fertilizer applications during the NEM season. Farmers in the study region mainly planted the maize cultivars COH3 and COH(M)5 (ref. 2). The crop models were calibrated for these cultivars by using experimental field data collected at TNAU field sites. Survey reports indicated that the plant population normally adopted by farmers in the region varied from 60,000 plants/ha to 80,000 plats/ha, depending on each farmer's respective plant geometry. Survey results indicated large differences in the amount of fertilizer applied by farmers: of the 60 farmers surveyed, three farmers used less than 150 kg of nitrogen ha^{-1}; 30 farmers used 150–200 kg of nitrogen ha^{-1}; and 27 farmers used more than 200 kg of nitrogen ha^{-1} (ref. 2). However, all the farmers applied nitrogen in the form of urea, split between three applications: 25% at basal; 50% at 30 days after sowing; and 25% at the flowering stage. The actual quantity of nitrogen fertilizer applied by each farmer was used in setting up the crop model experiments to better capture the heterogeneity among the farms[2].

APSIM and DSSAT/CERES-Maize were calibrated for maize cultivars COH3 and COH(M)5 in the study region using experimental field data collected at sites belonging to Tamil Nadu Agricultural University, Coimbatore. Data were collected from six experiments – three were used for obtaining calibration data, and a separate set of three experiments were used for validating the genetic coefficients. For the COH3 maize cultivar, the sowing dates for each experiment included: 15/09/2000, 11/10/2000, 30/10/2000, 11/07/2001, 24/07/2001, 24/08/2001. For the COH(M)5 maize cultivar, the six sowing dates included: 15/07/2009, 30/07/2009, 15/08/2009, 15/07/2010, 30/07/2010, 15/08/2010 (ref. 2).

Plant parameters and physiological characteristics in these crop models are given in the form of genotype coefficients, which describe physiological processes such as development, photosynthesis and growth for individual crop varieties. In the DSSAT/CERES-Maize model, the genetic coefficients for maize are summarized in Table 1: P1, the thermal time from seedling emergence to the end of the juvenile phase; P2, the extent to which development, expressed in days, is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate; P5, the thermal time from silking to physiological maturity; G2, the maximum possible number of kernels per plant; G3, the kernel filling rate; and PHINT, the phylochron interval. The coefficients calibrated for simulating maize yield with APSIM (Table 2) include: the thermal times for emergence to end of juvenile (tt_emerg_to_endjuv); flowering to maturity (tt_flower_to_maturity); flowering to start of grain (tt_flower_to_start_grain units); maximum number of grains per head (head_grain_no_max in numbers); and grain growth rate (grain_gth_rate in mg/grain/day)[2]. The calibrations were achieved by iteratively changing the relevant coefficients to achieve the best possible match between the simulated and observed number of days to the phenological events and grain yield. There are small differences between some of the phenological parameter values for DSSAT/CERES-Maize and APSIM, which might be due to the different ways the two models parametrize crop growth, and their sensitivity to these parameters in achieving the best match to observations. These are continuing areas of research for the AgMIP[11], of which this study is a part, and larger coordinated analyses are underway to highlight and better understand differences between the models. Simulations performed with the final set of parameters for both the models indicated good relationship between observed and simulated days to flowering, days to maturity, and yield as shown by the best-fit lines for each model in Figure 2 (ref. 2).

The calibration efficiency has been evaluated using the root mean square error (RMSE) and coefficient of determination (R^2), which are presented in Table 3 (ref. 2). Overall, the DSSAT/CERES-Maize simulations for the COH(M)5 and COH3 cultivars showed relatively high R^2 values (>0.5) for days to anthesis, days to physiological maturity, and yield (kg/ha), which indicate good agreement between observed and model simulated data[19]. DSSAT/CERES-Maize RMSE values for the major phenological stages (measured in days) and yield (kg/ha) were relatively low (below 13% deviation) and largely similar between the cultivars, also indicating the models' relatively good predictions[2,20]. Similarly, the results of the APSIM calibration also show reasonable predictability, although it did show somewhat smaller R^2 values than DSSAT/CERES-Maize for days to anthesis, physiological maturity and yield. Compared to DSSAT/CERES-Maize, the APSIM RMSE values for the COH(M)5 cultivar phonological stages are smaller, however the RMSE for grain yield is slightly higher.

The soil inputs were obtained from a representative soil profile sample and were described by layer, inclusive

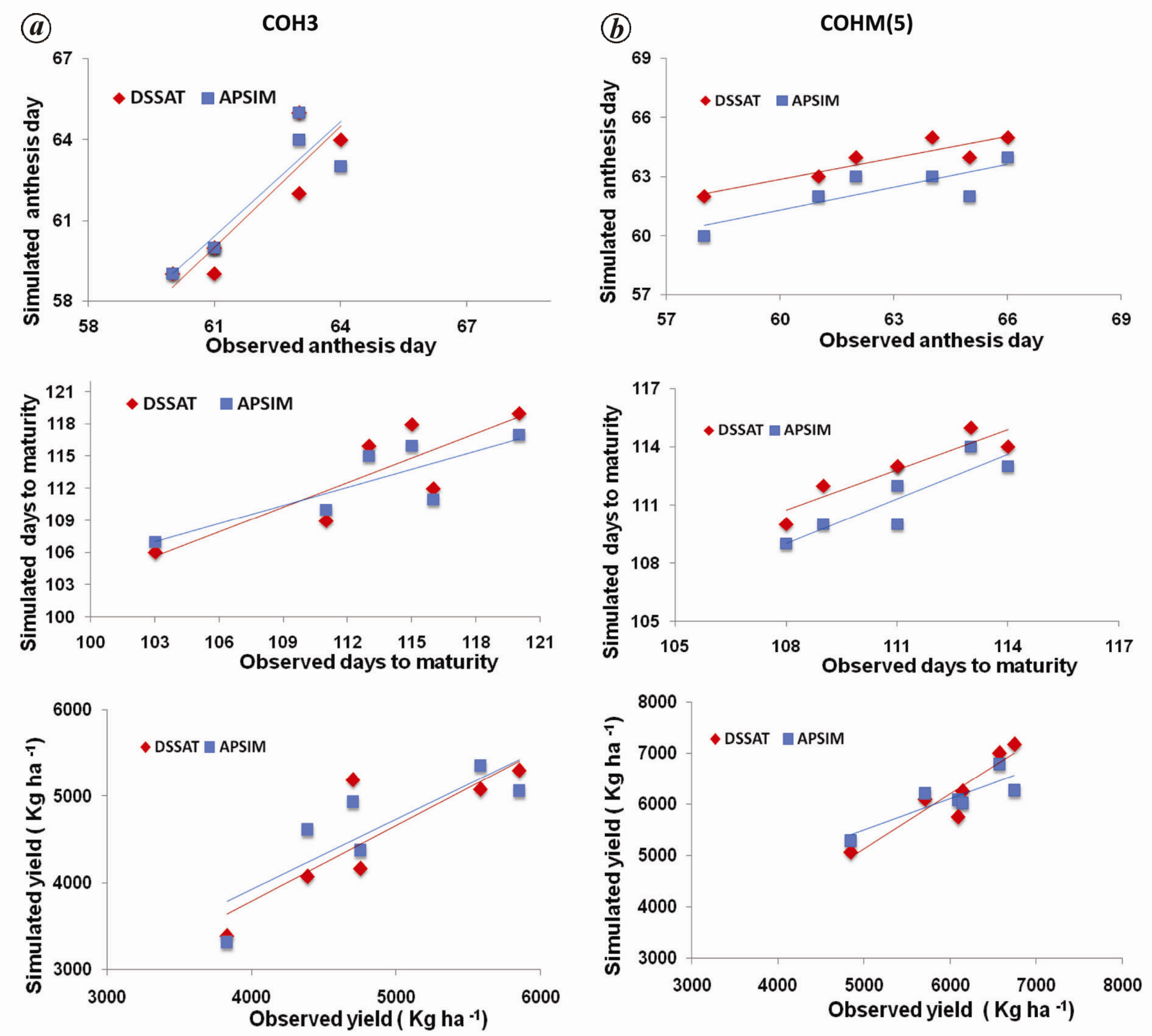

Figure 2. Best-fit lines obtained for the genetic coefficients that gave the best match between simulated and observed days to flowering; maturity; and yield for two cultivars (***a***) COH3 and (***b***) COHM(5). Credited to Ponnusamy *et al.*[2].

Table 1. Genetic coefficients for cultivars of maize in DSSAT/CERES-Maize model

Cultivar	P1	P2	P5	G2	G3	PHINT
COH3	310	0.530	900	600	7.90	38.3
COH(M)5	330	0.520	860	769	8.50	38.8

P1, Thermal time from seedling emergence to the end of the juvenile phase.
P2, Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate.
P5, Thermal time from silking to physiological maturity.
G2, Maximum possible number of kernels per plant.
G3, Kernel filling rate. PHINT, Phylochron interval credited to Ponnusamy *et al.*[2].

of the physical, chemical, and morphological properties of the soil surface and each soil layer within the root zone[2]. The Coimbatore study region had two major soils comprised of clay and sandy loam. Clay soils had a depth of 138 cm, with a drainage lower and upper limits of 0.24 and 0.44 $cm^3 cm^{-3}$ respectively. The bulk density ranged from 1.14 to 1.25 g cm^3, the cation exchange capacity ranged from 21.6 to 26.2 cmol kg^{-1}; and soil organic carbon ranged from 0.48% to 0.83% over the soil layers[2]. Sandy soils had a depth of 52 cm with drainage lower and upper limit of 0.13 $cm^3 cm^{-3}$ and 0.25 $cm^3 cm^{-3}$ respectively. The cation exchange capacity ranged from 9.2 to 15.9 cmol kg^{-1}, and soil organic carbon ranged from 0.48% to 0.6% over the soil layers[2].

Figure 3 *a* shows the baseline yields as simulated by DSSAT/CERES-Maize and APSIM. Though differences can be observed in the outlying values, these baseline simulation means are not significantly different, and have similar median values. There is a fairly large range between the 60 farmers in both simulations, and this is primarily attributed to the variation in management practices by individual farmers. Additionally, the standard deviations for each farm's yield (Figure 3 *b*) from 1980–2010 are higher as simulated by DSSAT/CERES-Maize than by APSIM, suggesting that APSIM does not simulate as much interannual variability in response to the annually varying climate as DSSAT/CERES-Maize does.

Table 2. Genetic coefficients for maize cultivars in APSIM model

Cultivar	1*	2*	3*	4*	5*
COH3	330	845	117	793	4.6
COH(M)5	450	910	100	510	6.5

[1]*Time from emergence to end juvenile. [2]*Time from flower to maturity. [3]*Time from flower to start grain units. [4]*Max head grain no. [5]*Grain growth rate credited to Ponnusamy *et al.*[2].

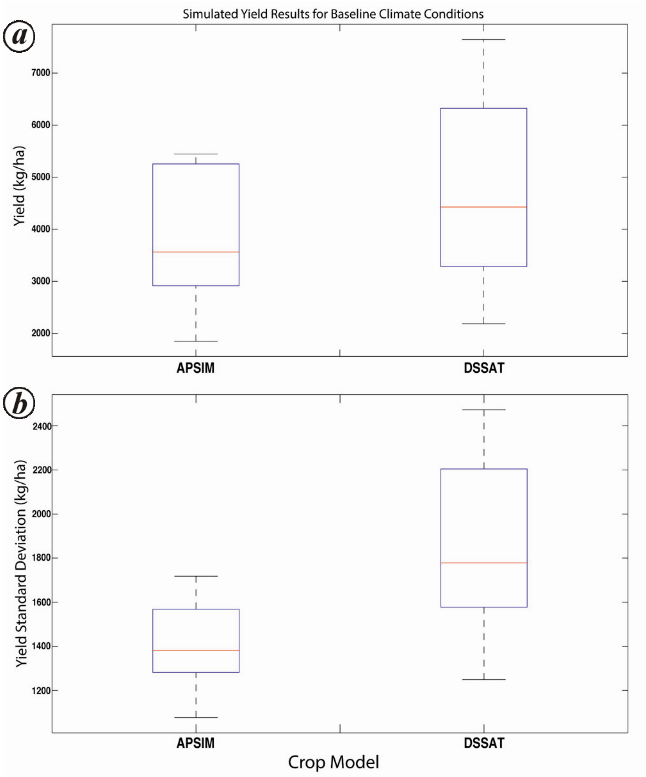

Figure 3. ***a***, Baseline simulated yields (kg/ha) over 60 farms in Coimbatore district as simulated by DSSAT and APSIM. ***b***, Base-line simulated yield standard deviations over 60 farms in Coimbatore district as simulated by DSSAT and APSIM.

Baseline climate data and future climate scenarios

A daily baseline weather series for the Coimbatore district was obtained from the Tamil Nadu Agricultural University weather observatory, and included with solar radiation, maximum daily temperature (T_{max}), minimum daily temperature (T_{min}), rainfall and relative humidity from 1980–2010. The dataset was completed with vapour pressure, windspeed and dewpoint temperature, as calculated by the AgMIP Climate routines, available with the AgMIP Protocols[21]. To create a comparable weather file for each of the 60 farm sites, the observatory data underwent a mean 'bias adjustment' using the monthly WorldClim climate dataset with high spatial resolution (5 km) to obtain more representative values for the 60 farms sites[21,22]. Though the mean values of these adjusted datasets may better reflect the 60 farm sites, the intra-seasonal and inter-annual variability in the agro-climatic variables is maintained.

The AgMIP Climate Team Protocols[21] largely informed the creation of the future climate projections. To summarize, future climate projections were obtained by using the fifth Coupled Model Intercomparison Project (CMIP5) and the Representative Concentration Pathways for carbon emissions currently in use by the IPCC Fifth Assessment Report. Future climate projections were created by utilizing a 'delta' approach, in which the mean monthly changes in important agro-climatic variables were calculated by taking the difference between the RCP8.5 climate scenario and simulated baseline conditions. These monthly mean agro-climatic changes, or deltas, were then applied to the daily baseline weather series for each respective month. The future climate series and the corresponding projected carbon dioxide concentration from RCP8.5 were then used in crop model simulations. For the scope of this study, we focus on the impacts related to the RCP8.5 mid-century (centered on 2055) future climate scenario. We refer to these future projections as 'mean change scenarios'. This procedure was repeated for 20 of the CMIP5 GCMs, however, five GCMs were selected for their adequate representation of the climatic processes important in simulating the general Asian monsoon system, such as the spatial distribution of monsoon rainfall and the response of the monsoon system to various modes of climate variability, and general acceptance and wide use throughout the climate modelling community[21]. These models include the Community Climate System Model 4.0 (CCSM4)[23]; the Geophysical Fluid Dynamic Laboratory Earth System Model (GFDL-ESM2M)[24], the UK Met Office Hadley Centre Earth System Model (HadGEM2-ES)[25], the Model for Interdisciplinary Research on Climate v5 (MIROC5)[26] and the Max Planck Institute for Meteorology Earth System Model (MPI-ESM-MR)[27].

Table 3. Model statistics

		Days to anthesis		Days to maturity		Grain yield (kg/ha)	
Model	Model stat.	COH 3	COH(M)5	COH 3	COH(M)5	COH 3	COH(M) 5
DSSAT	R^2	0.80	0.82	0.71	0.84	0.73	0.85
	RMSE	1.35	2.12	2.83	2.04	490	351
APSIM	R^2	0.65	0.81	0.56	0.64	0.66	0.64
	RMSE	2.27	1.41	3.58	1.78	439	430

Credited to Ponnusamy *et al.*[2].

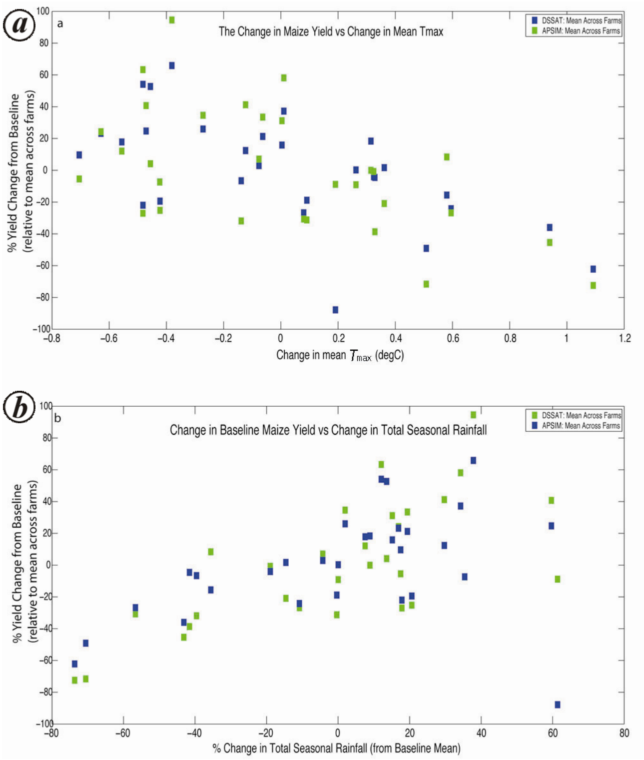

Figure 4. The across–farm mean percentage change in yield from the simulated baseline for DSSAT and APSIM, plotted against (***a***) the change in mean T_{max} from the baseline mean, and (***b***) the percentage change in total seasonal rainfall from the baseline mean.

Results

Simulated yield response to baseline climate conditions

The baseline climate was evaluated for the NEM season, spanning October–November–December. For most of the climate variables, except for T_{min} (not shown), no significant trends were identified during the baseline period. Similarly, no significant strong trends were found in the 1980–2010 simulated yields at the farm sites by either DSSAT/CERES-Maize or APSIM. Over the 1980–2010 timeseries, the relationships between yield and several agroclimatic variables were assessed, and the strongest correlations were found between yield and mean T_{max}, and yield and total seasonal rainfall. For example, the median farm simulated by APSIM showed correlation values of (Pearson's) $r = -0.48$ and $r = 0.44$ between yield and mean T_{max}, and yield total seasonal rainfall respectively. The median farm simulated by DSSAT/CERES-Maize showed correlation values of $r = -0.44$ and $r = 0.61$ between yield and mean T_{max}, and yield and total seasonal rainfall respectively.

Figure 4 better highlights the relationship between baseline yield and mean T_{max} and total seasonal rainfall, and contextualizes the yield responses that might occur with future climate change. The average percentage yield change across farms for DSSAT/CERES-Maize and APSIM is plotted against the change in mean T_{max} (Figure 4 *a*) and in total seasonal rainfall (Figure 4 *b*). Figure 4 *a* shows that as mean T_{max} increases incrementally, there are significantly correlated reductions in yield from the baseline mean: DSSAT/CERES-Maize displays a Pearson's $r = -0.45$; while APSIM displays a Pearson's $r = -0.54$ (both *P*-values below 0.02). In contrast, when the percentage change in yield is plotted against the percentage change in total seasonal rainfall from 1980–2010 average, a significantly correlated increase in yield is found for both crop models: DSSAT/CERES-Maize displays a Pearson's $r = 0.69$; while APSIM displays a Pearson's $r = 0.43$ (again, both *p*-values well below 0.02).

Simulated yield response to baseline climate conditions with adaptation options

We expect agricultural systems to develop with time, such that climate change will impact future modified agricultural systems that have taken advantage of various adaptation strategies. However, it is also possible that by implementing various adaptations and crop management strategies, farmers may see benefits under current (baseline) climatic conditions. Quantifying the yield impacts of various adaptation strategies under baseline conditions can help to better contextualize their true efficacy under future climate change conditions[28]. Figure 5 shows the percentage change (from baseline yield) for three adaptation strategies tested in this study: (a) an earlier date of sowing; (b) the application of an extra 20% dosage of nitrogenous fertilizers; and (c) the application of 50 mm of supplemental irrigation during the flowering stage. Both the APSIM and the DSSAT/CERES-Maize models show median farm yield increases of 20% and above, although APSIM displays a larger range of response across the 60 farms to the sowing date adaptation strategy. Adding additional fertilizer had very minimal effects on the modelled yields and yield variation, across the farms. Adding supplemental irrigation improved maize yields for a majority of the farms, a consistent finding between both crop models, and both models show a smaller inter-quartile range than when compared to altering the sowing date.

Simulated yield response to mean climate changes

Figure 6 shows box and whisker plots of the mean temperature and precipitation changes projected by 20 GCMs. They generally showed increased temperatures throughout the year, and increases in NEM rainfall in the Coimbatore District, while rainfall during the SWM is not shown to increase substantially. However, some of the 20 GCMs also indicated declines in rainfall, and so there is some uncertainty in these projections. The GCMs do largely agree that Coimbatore will experience a significant warming throughout the year (Figure 6 *a*). However, there is a 2–3°C spread between the projected increases, with MIROC5 showing the smallest increase in temperature, and the HadGEM2-ES showing the greatest warming (Figure 7). Furthermore, minimum temperatures (not shown) are also projected to increase by all the GCMs, and the magnitude of increase in minimum temperature was considerably higher compared to maximum temperature.

Figure 7 shows the spread in the projected temperature and rainfall changes (from baseline) simulated by 20 GCMs during the NEM. All models show a warming, while the precipitation response is decidedly more uncertain. The intersecting black lines indicate the threshold of

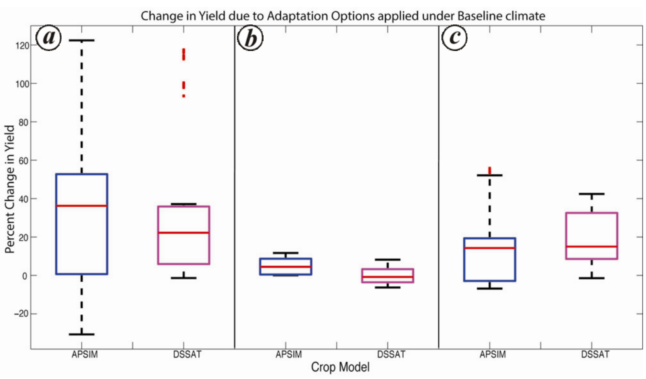

Figure 5. The percentage change in yield across 60 farms as simulated by the APSIM and DSSAT for the following adaptation options tested under baseline climate conditions: ***a***, earlier date of sowing; ***b***, the application of fertilizer at critical stages; ***c***, irrigation applied at critical stages.

change considered significant (using a *Z*-test and 30 growing seasons of climate data, taken for the 0.05 significance level) for temperature and rainfall[21]. While all temperature changes are significant, 11 of the GCMs show insignificant precipitation changes, while 9 display significant rainfall changes.

The projected mean climate changes from the GCMs were applied to the 1980–2010 baseline climate series and used in the APSIM and DSSAT/CERES-Maize simulations to evaluate the mean-change climate impact on current crop production. Figure 8 shows the relative yield change across the 60 farms as simulated by APSIM and DSSAT/CERES-Maize for each of the five chosen GCMs. There are some very apparent differences between the crop model simulations. In general, DSSAT/CERES-Maize shows a larger spread amongst the farmers, and shows substantial yield gains with median values comparable across the GCMs. DSSAT/CERES-Maize simulated yield losses do not exceed 10%. APSIM, on the other hand, shows a smaller inter-quartile range between the farms and, generally, more yield losses, particularly when using the mean climate changes from the CCSM4 and the MPI-ESM-MR. However, few farms as simulated by APSIM showed non-trivial yield gains in the upper percentile (MIROC5, GFDL-ESM2M, and HadGEM2-ES), and MIROC5 showed median farm yield increases. Table 4 shows the change from baseline in mean T_{max} and the percentage change in total seasonal rainfall for the five GCMs being considered, as these were shown to be moderately to highly correlated with baseline yields. Also shown in Table 4 are the average percentage changes in yield across the 60 farms as simulated by DSSAT/CERES-Maize and APSIM. The average yield changes are consistent with the results discussed above, and again indicate the contrary responses between DSSAT/CERES-Maize, which indicate substantial yield gains, and APSIM, which simulates yield declines, though with a smaller magnitude of change. Only with the MIROC5 GCM, which had a 17.7% increase in rainfall but the lowest increase in temperature of the GCMs at 0.63°C, did both crop models show increased mean yields across the farms.

Simulated yield response for the 'adapted' agricultural system to mean climate changes

We revisit the adaptation strategies tested here, but now simulate them under future climatic conditions. Figure 9 represents the yield change due to adaptation strategies when applied under future climatic conditions and compared to future yields (without adaptation). Here the yield impacts are more modest – an altered date of sowing and the strategic application of irrigation water at critical stages produced higher yield gains across the farms and climate models than applying additional fertilizer. The response between the crop models was quite similar, and

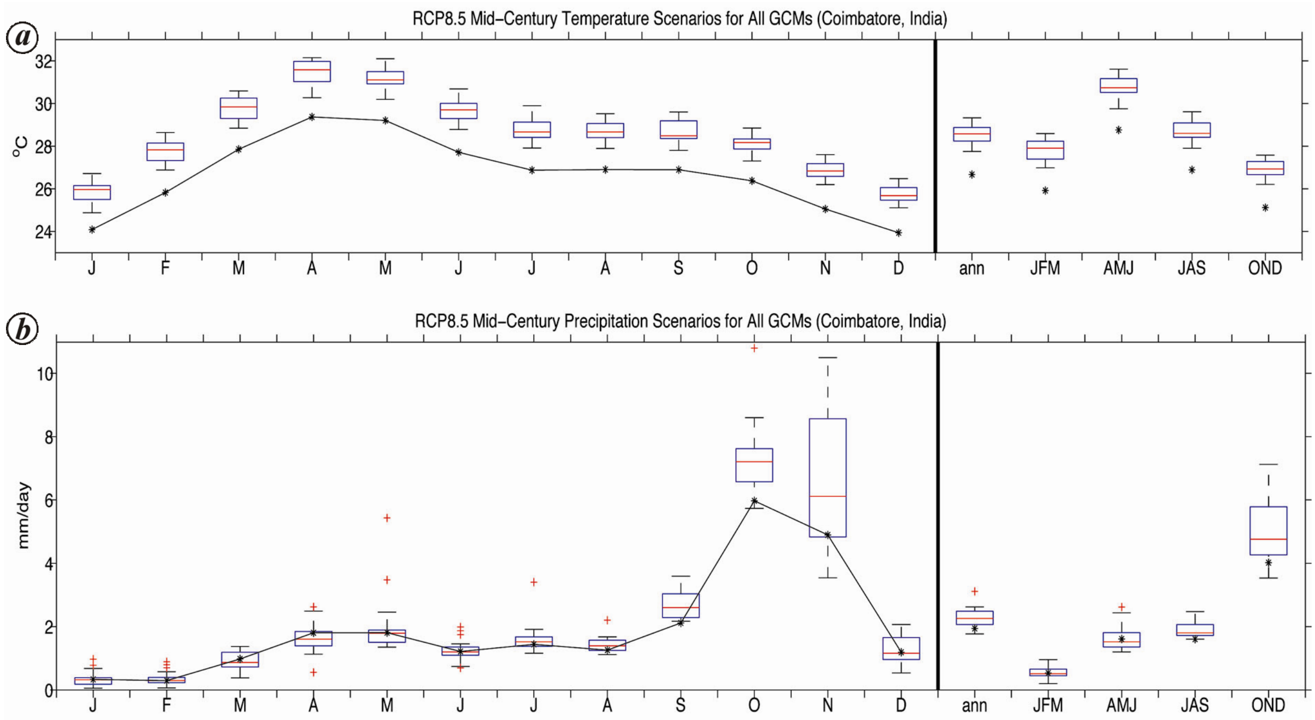

Figure 6. Projected changes in monthly mean (***a***) temperature and (***b***) rainfall for RCP 8.5 Mid-Century in Coimbatore. Black lines and stars indicate the baseline climate and the box-whisker plots show the spread in projections amongst the 20 GCMs taken from CMIP5. Averages for the annual (ann), January–March (JFM), April–June (AMJ), July–September (JAS), and October–December (OND) are shown at the far right of each plot[2].

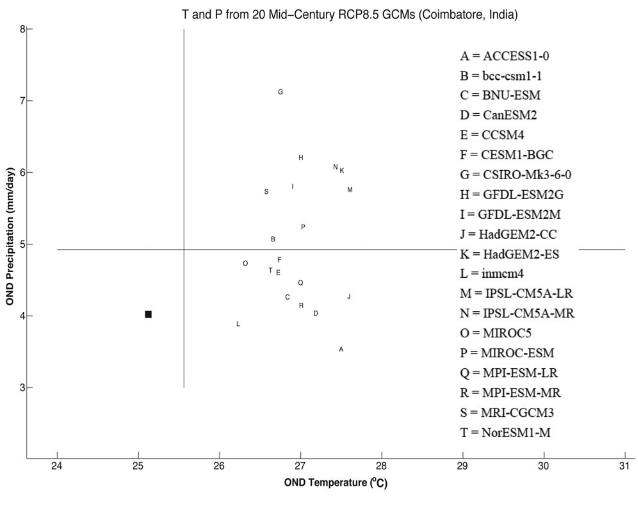

Figure 7. Projections for NEM rainfall and mean temperatures under RCP 8.5 Mid-Century climate conditions in Coimbatore. Black lines indicate calculated significance thresholds (at the 0.05 level), beyond which the temperature and rainfall changes become significant. The black square indicates the baseline temperature and seasonal mean rainfall[2].

adding irrigation additionally resulted in a slightly larger interquartile range between the farms, while an earlier date of sowing showed a larger number of 'outlier' farms, and a smaller range.

Evaluating the efficacy of adaptation strategies under future climate conditions

Lastly, we evaluate the efficacy of these strategies by comparing adaptation applied under future climatic conditions with adaptation applied under baseline climatic conditions (Figure 10). To do this, we utilize the recommendations presented in Lobell[28], in which we take the difference between the impact of the adaptation strategy under baseline conditions (i.e. the percentage change in yield as simulated without adaptation) and the impact adaptation conferred under future climate conditions. Ultimately, we are interested in assessing how much bigger or smaller the impact of adaptation was between current and future levels of climatic stress[28]. Figure 10 shows these results across farms for the three adaptation strategies tested. With an earlier date of sowing, we find consistency between the crop models and across the climate models in their reduced efficacy amongst most of the farms under future climatic conditions (compared to baseline conditions). APSIM showed a larger range between the farms than DSSAT/CERES-Maize, but there is a general agreement on the sign of change. Adding additional fertilizer resulted in somewhat different responses of APSIM and DSSAT/CERES-Maize. DSSAT/CERES-Maize showed small increases in the adaptation efficacy for the median farm and a range up to 6%, whereas APSIM

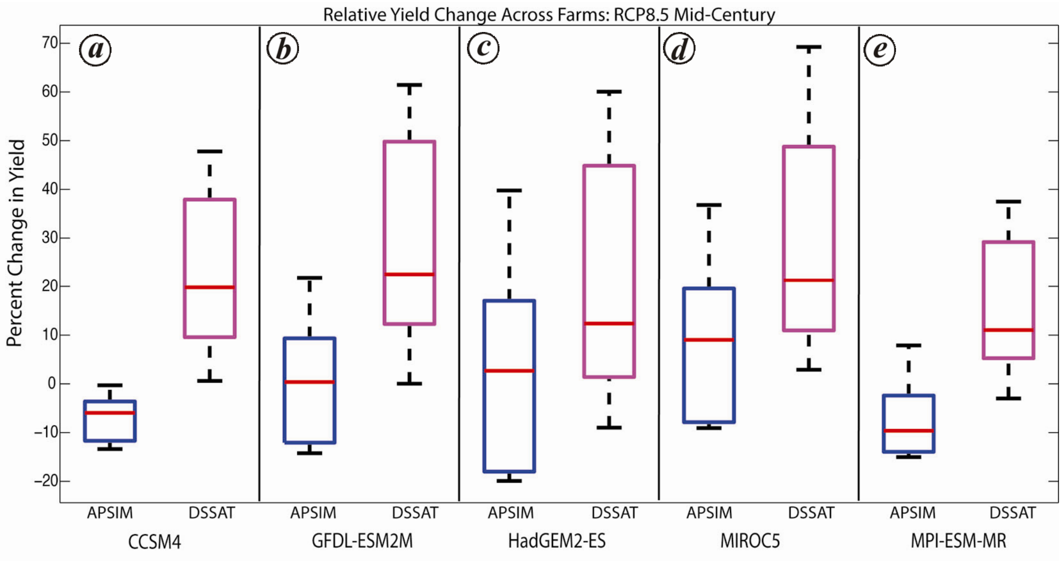

Figure 8. The percentage change in yield from the Baseline climate across 60 farms as simulated by the APSIM and DSSAT crop models for the GCMs (***a***) CCSM4, (***b***) GFDL-ESM2M, (***c***) HadGEM2-ES, (***d***) MIROC5 and (***e***) MPI-ESM-MR under RCP8.5 Mid-Century climate conditions (no adaptation strategies utilized).

Table 4. The change in mean T_{max}, total seasonal rainfall, and the corresponding maize crop model responses averaged over 60 farms in Coimbatore

GCM/Change in variable	CCSM4	GFDL-ESM2M	HadGEM2-ES	MIROC5	MPI-ESM-MR
Change in mean T_{max} (°C)	1.65	1.60	1.77	0.63	1.66
Change in total OND rainfall (% change from baseline)	14.6	44.1	49.6	17.7	3.5
Change in DSSAT yield (% change from baseline)	18.4	23.4	14.3	23.0	12.4
Change in APSIM yield (% change from baseline)	–8.4	–2.8	–3.6	3.5	–9.1

showed declines across all the farms of up to 14%. The crop models again displayed differences in their responses when supplemental irrigation was applied at critical stages. APSIM showed some small increases in efficacy across most of the farms, including the median farm, while DSSAT/CERES-Maize showed mostly small to moderate declines across the farms, and generally a larger range of results (with the exception of HadGEM2-ES).

Discussion

Baseline agroclimate analysis

Baseline yield simulations were not significantly different between APSIM and DSSAT/CERES-Maize, which produced similar median farm values. Generally, DSSAT/CERES-Maize produces more variability than APSIM amongst the simulated farm sites, which may indicate that DSSAT/CERES-Maize may be more sensitive to the heterogeneity in the farms' management strategies. Indeed, the diversity in management (e.g. fertilizer applications), soils, and non-weather environmental conditions could play a confounding role when interpreting the inter-farm variability in the baseline yields, and continued work will seek to isolate and understand these effects.

The relationship between the modelled baseline yields and mean T_{max} and total seasonal rainfall show how these agro-climatic variables may be important to regional maize growth. The yield–climate variable relationships shown in Figure 4 display fairly high and significant correlations, with substantial yield declines associated with even a degree of warming from the baseline mean (a smaller change than most mid-century projections). In contrast, there is also a strong positive relationship between yield and total seasonal rainfall, with DSSAT/CERES-Maize displaying a stronger correlation, and perhaps sensitivity to rainfall than APSIM. Future impacts to yield will actually be dependent on the interplay of the agro-climatic variables, as well as other non-climate variables, but such analyses can help modellers to identify the most important variables to consider under future climate change.

Applying adaptation under baseline climate conditions

Following the reasoning of Lobell[28], we evaluated our proposed adaptations under current climatic conditions to understand the benefits they may confer under present (climate) stress levels, and to more adequately assess

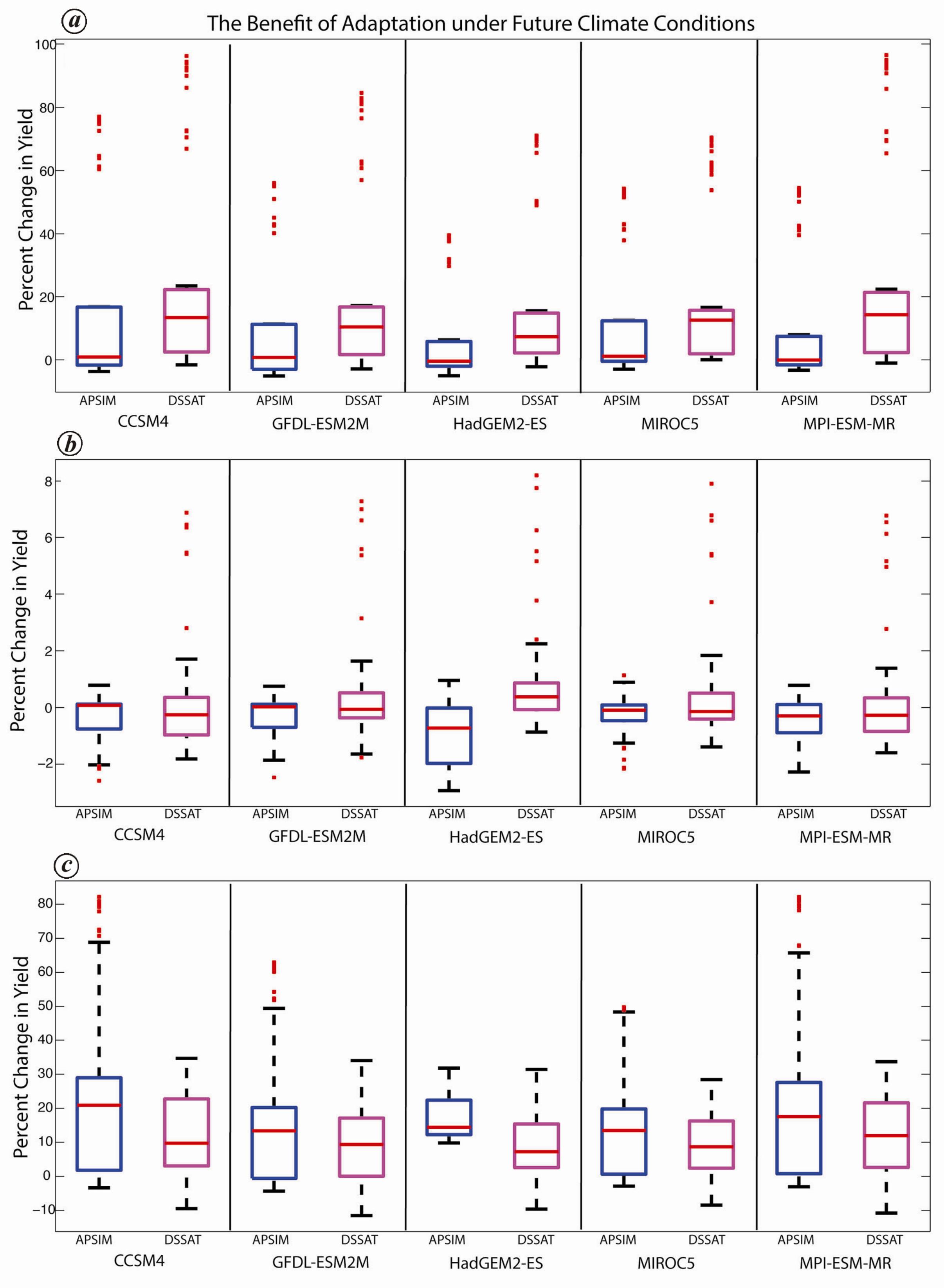

Figure 9. The relative yield change between crop simulations of the future climate with adaptation options and simulations of the future climate without adaptation for 60 farms, using the DSSAT and APSIM crop models. Simulations are shown for the following GCMs: CCSM4, GFDL–ESM2M, HadGEM2–ES, MIROC5, and MPI–ESM–MR under RCP8.5 Mid-Century climatic conditions. ***a***, The response to an earlier date of sowing; ***b***, application of additional fertilizer; ***c***, irrigation applied at critical stages.

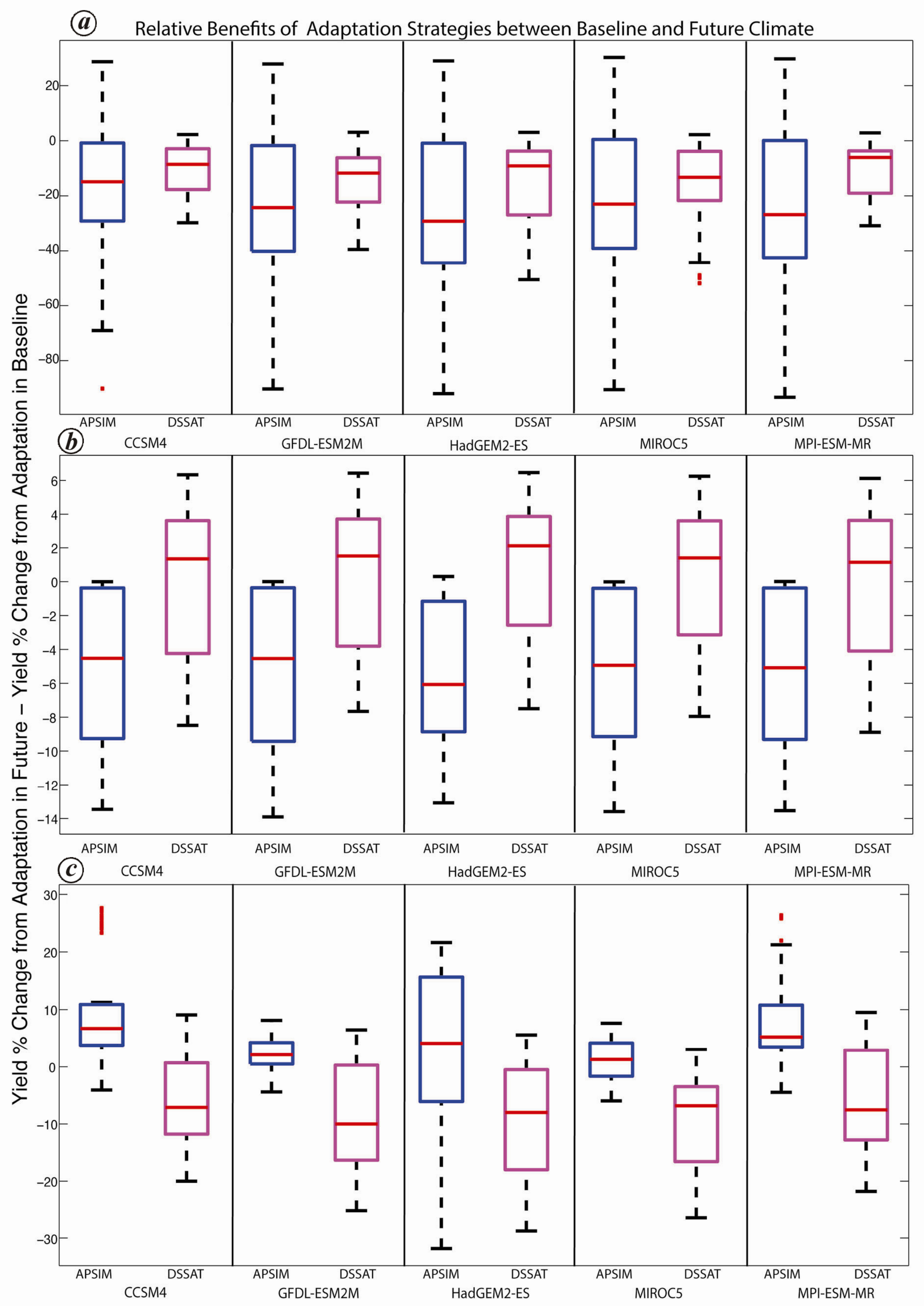

Figure 10. The relative benefits of adaptation strategies between Baseline and Future climates. For each adaptation strategy, an earlier date of sowing (***a***), application of additional fertilizer (***b***), and supplemental irrigation at critical stages (***c***), the boxplots show the percentage yield change resulting from adaptation applied in the future climate minus the percentage yield change resulting from adaptation applied in the baseline climate. The boxplots represent these results across the 60 farms in the Coimbatore District, and are shown for the following GCMs: CCSM4, GFDL–ESM2M, HadGEM2–ES, MIROC5, and MPI–ESM–MR run with RCP8.5 Mid-Century climate conditions.

their efficacy under future climate stress levels. Under current conditions, most of the farms benefited from an earlier date of sowing and from supplemental irrigation provided at critical stages of growth. In the former strategy, APSIM simulated a wide spread amongst the farms, although most of the farms generally saw substantial yield gains. Given this wide range of results, the actual benefit conferred by an earlier sowing date in APSIM may also depend upon the other attributes of an individual farm's management. In contrast, DSSAT/CERES-Maize showed a smaller amount of variability amongst the farms in their response, but no farms showed significant declines in yield, suggesting that all the farms, despite their unique management, could see at least some benefit. DSSAT/CERES-Maize and APSIM showed similar moderate responses to supplemental irrigation, with no farms experiencing significant declines. However, the average farm gain simulated with APSIM was not as high as compared to an earlier date of sowing, while the gains for DSSAT/CERES-Maize were comparable between the two strategies. In reality, a combination of these two strategies might be employed under current conditions to obtain full yield benefits, as both models show yield improvements of varying degrees. Neither model simulated substantial benefits, or losses with additional fertlizer, suggesting that this strategy may not be as effective as the other two tested under current climate conditions.

The relative differences in the responses of DSSAT/CERES-Maize and APSIM to water availability, and other agricultural inputs and management strategies, are currently under investigation in extensive AgMIP multimodel intercomparisons to improve and better apply crop models to impacts assessments. There is also a need for additional coordinated observed field data to validate and/or affirm which results are the most regionally representative.

The impact of future climate change

The APSIM and DSSAT/CERES-Maize responses to future climate changes as projected by the subset of five GCMs showed some significant differences. From Table 4, we find that only the MIROC5 GCM, which displayed the lowest temperature increase and a relatively moderate increase in rainfall, produced yield gains for the baseline in both crop models. For every other GCM, APSIM displays average yield declines despite substantial increases in rainfall. The highest rainfall increases, shown for the GFDL-ESM2M and the HadGEM2-ES, show the lowest yield declines. This is consistent with the correlations displayed in Figure 4, in which APSIM was more highly correlated with temperature than DSSAT/CERES-Maize, and more highly correlated with temperature than rainfall. Interestingly, similar responses for APSIM can be found in different regions, operating under different climate regimes. For example, Lobell *et al.*[29] found that increasing temperature (and, in tandem, extreme degree days >30°C) was more impactful on summertime US maize growth than reductions in rainfall, as the temperature increases induce water stress via increasing the vapour pressure deficit, which the authors note is not explicitly included in computing the water demand in DSSAT/CERES-Maize[30]. However, that study was conducted for climate conditions that increased temperature, but without concurrent increase in rainfall, which is projected for southern India. In the context of their study, Lobell *et al.*[29] posit that large rainfall changes are needed in order for APSIM maize growth to display sensitivity to rainfall. Some of our climate models show rainfall changes in excess of 40% increases, and yet yield declines in response to temperature persisted for most of the farms simulated. Therefore, we stress that more sensitivity testing is needed to identify if large increases in rainfall, or rainfall timing and distribution, could partially mitigate loss due to high temperature increases. Overall, APSIM maize simulations in this region may be more sensitive to temperature than rainfall, and more work will be undertaken to establish if these rising temperatures induce water stress, despite the increased rainfall. In stark contrast, DSSAT/CERES-Maize shows substantial yield gains, largely due to increased rainfall, and despite the temperature increases, to which it may not display the same sensitivity at APSIM[29]. Again, this suggests that DSSAT/CERES-Maize has an increased sensitive water response relative to APSIM, which is also consistent with the relationships discussed in Figure 4, our baseline agro-climatic assessment.

Across the farms shown in Figure 8, APSIM generally appeared to be less sensitive to the mean climatic changes imposed, showing median values close to zero or within –10% to +10% change across the 60 farms for most GCMs. Generally, where the temperature increases were high, and the rainfall increases were relatively low, APSIM showed declines across most of the farms. By contrast, DSSAT/CERES-Maize simulated a larger range of responses across the farms for all GCMs, though generally most farms experienced gains owing to the increased rainfall. The HadGEM2-ES had the highest temperature increases, to which DSSAT/CERES-Maize responded with small yield declines of under 10%, but the median farm values were consistently well above zero. There is a need to understand how representative these responses are of observed sensitivities, as the results of this study suggests that the impacts of climate change are significantly different depending on whether water or temperature is considered a more limiting factor.

Evaluation of adaptation options between baseline and future climates

In order to appropriately represent the impact of adapation between the baseline and future climates, we follow the methodology proposed in Lobell[28], which evaluates the difference in impact (in our case, percentage yield change) between adaptation applied in the future and adaptation applied in the baseline (Figure 10). There were few additional benefits conferred by an earlier sowing date, and all the GCM-crop model combinations show negative median values, indicating that the efficacy of the sowing adaptation is reduced when applied under future climatic conditions (compared to when it is applied under baseline climatic conditions). When additional fertilizer adaptations are tested, DSSAT/CERES-Maize shows a slightly more positive response, but the additional gains by applying this adaptation strategy under future climatic conditions are all under 10%, suggesting that its efficacy under future climatic conditions is more limited. APSIM differs in this result, and again shows a lesser impact of added fertilizer under future conditions than when compared to baseline conditions. The impact of added water through supplemental irrigation has a mixed response among the models as well. APSIM responds more favourably to added irrigation water, with median farm values showing larger gains under future climatic conditions than under baseline climatic conditions, which is interesting given that the response to increased rainfall with climate change overall was quite small compared to DSSAT/CERES-Maize (and even resulted in some declines). Given the discussion above, if APSIM's response is in fact partially governed by an increased water stress due increased temperatures, the deliberate addition of supplemental irrigation timed with important crop growth stages may act to alleviate some of this stress. Follow-up assessments to this study will better characterize this response to adaptation. DSSAT/CERES-Maize, on the other hand, shows marginal benefits, and mostly decreases in the benefits conferred by applying supplemental irrigation under future climate conditions (compared to when supplemental irrigation is applied under baseline climate conditions).

All three maize adaptation strategies tested, which rely on modifying on-farm production management rather than incorporating technological developments or transformative changes, appear to have limited added value under future climatic conditions for most of the farms simulated, compared to when they are tested under baseline climate conditions. This result is consistent with findings from other more generalized studies such as Challinor *et al.*[31], in which a number of yield impact studies were summarized to find that adaptation (in many forms) did not appear to significantly improve, or counteract, the losses incurred at tropical maize sites. Some of the yield gains under the baseline climatic conditions simulated here would suggest that an earlier date of sowing and supplemental irrigation are useful strategies to adopt under the current climate, particularly in combination, but new strategies with greater efficacy under future conditions may need to be developed to administer in this region.

Limitations and uncertainty

Based upon the results presented here, it would appear that APSIM displays a greater sensitivity to temperature increases, while DSSAT/CERES-Maize is more responsive to rainfall increases in this domain – both climatic changes are robustly projected in future climate simulations conducted by GCMs, although recent studies are more deeply exploring just how representative these projections actually are in the context of current monsoon rainfall trends[6]. Follow-up work to this study will further investigate the baseline and future variability in important agro-climatic variables, such as the mean $T_{\max}$ shown here, but also in the monsoon onset and intra-seasonal rainfall distribution, to which yields may also display sensitivity currently and/or in a warmer future.

However, the substantial differences in yield response shown here between DSSAT/CERES-Maize and APSIM suggest that the crop models may introduce more uncertainty into South Indian climate–agriculture impact assessments than the global climate models, which largely agree on the sign of change for major agro-climatic variables. The differences in the processes parametrized and incorporated in these crop models warrant further evaluation, and are currently under investigation in a variety of AgMIP crop model intercomparisons[32]. In addition to sensitivity assessments, we call for additional validation and comparison at each AgMIP regional research sites, such as the Coimbatore District, to observed field data, preferably over multiple years, in order to better check the model performance.

Some uncertainty is also introduced by the heterogeneity in management practices amongst farmers, noted in Figure 3, where fairly wide ranges exist in the baseline yield simulations across farms. Further exploration is therefore warranted of the yield response sensitivity to the different types of management across the farms. For example, future work building upon this study may group the farmers according to their fertilizer usage, for which we identified at least three distinct groupings of fertilizer amounts in Section 2, so that the sensitivities and variabilities of yield response to climatic changes within one 'fertilizer group' can be assessed. This could be further compared to model-based sensitivity experiments that vary over fertilizer application levels to understand if and how models may be capturing the 'observed' sensitivity. Likewise, farmers could also be grouped by various socio-economic metrics, such as farm income, poverty level, etc. (for which fertilizer applications may be correlated), and the differences in crop-response that arise from socio-economic conditions could be further explored. Such findings could lend themselves to design adaptation strategies targeting the most needful farms.

Given the ongoing need to understand the differences between these two crop models, the findings of this study do not present conclusive evidence as to which model more adequately captures the impact of climate change on the maize yields in Coimbatore. Rather, this is among the first studies comparing crop–maize–yields between different models in southern India, in the context of both baseline and future climatic conditions. We believe these results highlight the disparate responses between the crop models that had not been visualized before for this region/district, under conditions of both increasing temperature and rainfall. However, this is a necessary illustration of uncertainty that warns against utilizing just one crop model for climate–impacts assessments, and identifies areas for targeted research to understand these models' discrepancies.

Despite the differences in modelled yield response to future climatic conditions, perhaps one of the more general findings across all the climate and crop models was the lack of significant improvement in the efficacy of the tested adaptation options under future climatic conditions. Altering the sowing date and applying supplemental irrigation did appear to produce some yield improvements when applied under baseline conditions for both crop models (although there was some variation across farms), and these might be management strategies currently worth incorporating. However, the gains of applying these adaptations under future climatic conditions diminished substantially, and in a large portion of the farms – across both crop models and for all GCMs – there was actually less of a gain under future climatic conditions than under baseline climatic conditions (for a few farms, there were even losses in yield due to the imposition of adaptation, as was also noted for some of the tropical maize sites detailed in Challinor *et al.*[31]). This study did not incorporate current technology trends or yield improvements that are expected to occur outside specific efforts to adapt to climate change, but such explorations are currently underway to better understand how these impact the efficacy of future climate change adaptations[2]. However, the adaptation results presented here would suggest that new, perhaps more transformative, adaptation strategies may be needed in this region, particularly if the projections for increased rainfall are accurate, as there may be ways to take advantage of such a change (by using improved varieties, or planting different crops, or building more rainwater harvesting and irrigation infrastructures, for example).

Conclusions

This study utilized two widely-used cropping system models, APSIM and DSSAT/CERES-Maize, as well as five CMIP5 global climate models to understand the impact of climate change on maize yields in the Coimbatore District in southern India. Our study enables us to: (1) characterize how these models simulate baseline (1980–2010) maize yields and their sensitivity to important agro-climate variables; (2) evaluate the impact of climate change on maize yields using a multi-model approach; and (3) describe the efficacy of various adaptation strategies with respect to the baseline and the future climatic conditions, while also considering the sources of uncertainty introduced by these models and climate-crop systems. Overall, we found that DSSAT/CERES-Maize appeared more sensitive to changes in rainfall, while APSIM responded more to temperature increases under both baseline and future climatic conditions. The future climate projections were fairly robust across five GCMs, which showed increases in both rainfall and temperature. This led to different predictions of yield response to future climate changes, with APSIM showing yield declines and DSSAT/CERES-Maize showing yield improvements. The respective response of crop models to each GCM was largely consistent, even if the crop models did not agree on yield response. This suggests that these crop models may be a larger source of uncertainty in future yield assessments in this district than the global climate models. More sensitivity testing, coupled with observed data to help validate crop model simulations at the site, is required to understand which model most accurately represents the maize response in this region. We suggest that understanding the sensitivity of these models to temperature increases (and perhaps how this impacts water stress) while also including rainfall increases, could help to better identify the models' differences and improve them for maize simulations in southern India, or other monsoon domains where these climate projections may be similar. Such analyses are currently being undertaken by the AgMIP regional crop model intercomparisons, of which this study is an initial result. With respect to the adaptation options tested, generally, an earlier date of sowing and supplemental irrigation adaptation strategies seemed to bring positive yield results to most of the farms under baseline climate conditions. However, the efficacy, or gains of these adaptations were substantially diminished under future climatic conditions for both crop models despite their differences. This suggests that these types of simple on-farm management strategies may not be enough to combat future climate change in the region, or to take advantage of potential increases in rainfall, in the context of these simulations. Adaptation options with improved varieties or infrastructural investments to benefit from increased rainfall may yield better results as future adaptation strategies.

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