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Climate change impact uncertainties for maize in Panama: Farm information, climate projections, and yield sensitivities

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A B S T R A C T

We present results from a pilot project to characterize and bound multi-disciplinary uncertainties around the assessment of maize (*Zea mays*) production impacts using the CERES-Maize crop model in a climate-sensitive region with a variety of farming systems (Panama). Segunda coa (autumn) maize yield in Panama currently suffers occasionally from high water stress at the end of the growing season, however under future climate conditions warmer temperatures accelerate crop maturation and elevated CO_2 concentrations improve water retention. This combination reduces end-of-season water stresses and eventually leads to small mean yield gains according to median projections, although accelerated maturation reduces yields in seasons with low water stresses. Calibrations of cultivar traits, soil profile, and fertilizer amounts are most important for representing baseline yields, however sensitivity to all management factors are reduced in an assessment of future yield changes (most dramatically for fertilizers), suggesting that yield changes may be more generalizable than absolute yields.Uncertainty around GCMs' projected changes in rainfall gain in importance throughout the century, with yield changes strongly correlated with growing season rainfall totals. Climate changes are expected to be obscured by the large interannual variations in Panamanian climate that will continue to be the dominant influence on seasonal maize yield into the coming decades. The relatively high (A2) and low (B1) emissions scenarios show little difference in their impact on future maize yields until the end of the century. Uncertainties related to the sensitivity of CERES-Maize to carbon dioxide concentrations have a substantial influence on projected changes, and remain a significant obstacle to climate change impacts assessment. Finally, an investigation into the potential of simple statistical yield emulators based upon key climate variables characterizes the important uncertainties behind the selection of climate change metrics and their performance against more complex process-based crop model simulations, revealing a danger in relying only on long-term mean quantities for crop impact assessment.

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1. Introduction

The generation of decision support systems for climate change impacts relies on a long series of processes from data collection, data processing and numerical simulations, analysis of results, and interpretation for stakeholder use. Uncertainties exist in each process, and must be quantified to enable stakeholders to manage risk in designing adaptation strategies placing climate uncertainties in the proper background of regional and management variability (Iglesias et al., 2010; White et al., 2011). For each region and agricultural system it is likely that several sources of uncertainty act as crucial bottlenecks with larger influence on the final messages received by stakeholders, and therefore locating critical pieces of information can dramatically improve impacts assessment. This study examines a pilot climate change impacts for decision support process from start to finish, identifying these various sources of uncertainty and isolating areas where further research could dramatically improve outcomes.

A Mesoamerican pilot location for agricultural impacts was selected to directly inform two ongoing projects in the region. The NASA/USAID SERVIR project (http://www.servir.net last accessed

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June 29, 2011; Graves et al., 2005) delivers state-of-the-art NASA observations to Mesoamerican users for applications including agriculture, water resources, health, and flash-flood relief. A NASA GISS/Columbia University/University of Florida project is also underway to provide decision support for climate change impacts on agriculture across Central America and the Southeast United States using dynamic biophysical crop models, with results designed to be potentially included in SERVIR's online resources. We selected maize (*Zea mays*), a major commodity and important source of food in Mesoamerica, as the crop to be investigated, and a range of climate periods to be relevant to ongoing planning of agricultural policy and infrastructure as well as to provide longer-term scenarios where the climate change signal is more clearly separated from natural interannual to interdecadal variability. Giorgi (2006) identified the Central American region as a location where rainfall variability changes pose a substantial risk (more so than mean climate changes), although changes in both rainfall's mean and variability are projected to be more significant in the November–April dry (and less agriculturally important) season not analyzed here.

Dynamic process-based crop models resolve plant and environmental processes relevant to crop growth and are rooted in physical responses dependent on developmental stage and crop stresses that may interact in a non-linear manner. Unlike simple statistical regression models, process-based crop models are capable of simulating the impacts of climate conditions outside of observed historical ranges, including the effects of high carbon dioxide concentration ([CO_2]) environments. Resolution of these processes comes at the cost of spatial coverage – these crop models are run at a representative field rather than directly representing a wider region – and an onerous requirement of input data (described in the next section). These data are simply not available in many important agricultural regions or across the wide diversity of farming systems in many developing areas, but these regions still need a strategy to address climate vulnerabilities. This study examines whether the types and amount of required input data may depend on the application, as the crop model does not necessarily need to exactly capture baseline yields in order to investigate how yields respond to climate changes.

This work also explores the potential of future yield changes to be summarized by a strong response to projections of a small number of key climate change metrics. Recent studies have demonstrated the utility of visualizing climate impacts response surfaces based upon projected changes in temperature and rainfall across a wide range of plausible climate conditions to allow a rapid assessment of key sensitivities (e.g., Jones, 2000; Scholze et al., 2006; Morse et al., 2009; Fronzek et al., 2010; Räisänen and Ruokalainen, 2006), however non-linearities in the biophysical response to climate factors can lead to significant biases in some cases (Hansen et al., 2006; Schlenker and Roberts, 2006, 2009). The precision of impacts response surfaces regressed from crop model simulations is likely to depend on the crop, region, and degree to which yield changes are sensitive to particular climatic variables.

The results presented are a useful pilot exploration of uncertainty for the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig et al., 2012; this issue), which seeks to connect climate scientists, crop modelers, agricultural economics modelers, and information technology specialists to simulate agricultural production across the world's important agricultural regions for analysis of the linked economic impacts of climate change. The availability of high-quality soil, weather, cultivar, and agricultural management data reduces many of the uncertainties in the simulation of climate impacts on crop production, but are not always available in data-scarce areas. In addition, homogeneous areas with more intensive management, modern cultivars, and heavy use of mechanical equipment are more suited to crop model simulations based upon a single representative farm. This study examines the uncertainties that may be reduced if crop models are granted access to farm-level information and climate records to underscore the importance of local involvement in AgMIP and other crop modeling applications, and also to explore the transferability of climate impact projections from one particular farming system to another in a region with diverse agricultural practices.

2. Material and methods

2.1. The CERES-Maize crop model

Crop model simulations were conducted with the Crop Estimation through Resource and Environment Synthesis crop model (CERES-Maize), a component of the Decision Support System for Agrotechnology Transfer (DSSAT v4.5.0.047; Jones et al., 2003; Hoogenboom et al., 2010). DSSAT is a family of crop models that simulate daily crop development and complex interactions with the farm-level environment using biophysical processes that facilitate application outside of observed climate conditions. These crop model simulations require local weather data (daily rainfall, minimum and maximum temperatures, and solar radiation), a detailed soil profile, genetic coefficients describing the specific maize cultivar, and crop-management practices (e.g. planting dates and practices; irrigation and fertilizer applications). As of this writing only a few published studies could be identified that document maize model applications in Mesoamerica (e.g. Conde et al., 1997, in Mexico; Maytín et al., 1995; Jones and Thornton, 2003, using generalized cultivars and management for gridded assessment of all of Latin America), but these studies do not focus on uncertainty analysis and not all include [CO_2] effects. Crop model applications are also conducted at some national meteorological or agricultural agencies; however formal publication and documentation were not readily located.

2.2. Farm-level data collection and calibration

Panama was selected as a Mesoamerican pilot location due to its hosting of the headquarters for SERVIR Mesoamerica at the Water Center for the Humid Tropics, Latin America, and the Caribbean (CATHALAC) in Clayton, Panama. While dominant throughout Northern Mesoamerica (Nicaragua and north), maize production lags behind rice production in Panama but remains a prominent rainfed crop (USDA FAS, available at http://www.fas.usda.gov/psdonline, last accessed June 30th, 2011). Panamanian maize cultivation is concentrated on the eastern portion of the Azuero Peninsula that extends into the Pacific from the South of the country (Fig. 1a). To simulate this region, a representative weather series at Los Santos (7.95°N, 80.42°W) was provided by the Panamanian Electric Transmission Company (ETESA),[1] and a Panamanian Cambisol soil profile was drawn from the WISE database (Batjes and Bridges, 1994) to match the Harmonized World Soil Database (FAO, 2009) reported conditions (Fig. 1b).

Daily rainfall, maximum and minimum temperatures, and sunshine hours were collected for 1980–2009 to gauge baseline climate without being overly obscured by shorter term natural modes of variability (WMO, 1989; Guttman, 1989). Sunshine hours were converted to daily solar radiation and data gaps were filled in using the WGEN-based weather generator (Richardson and Wright, 1984) included in Weatherman (a component of DSSAT). Fig. 2 presents

[1] Global station datasets proved to have questionable rainfall totals and limited spatial coverage for our desired applications.

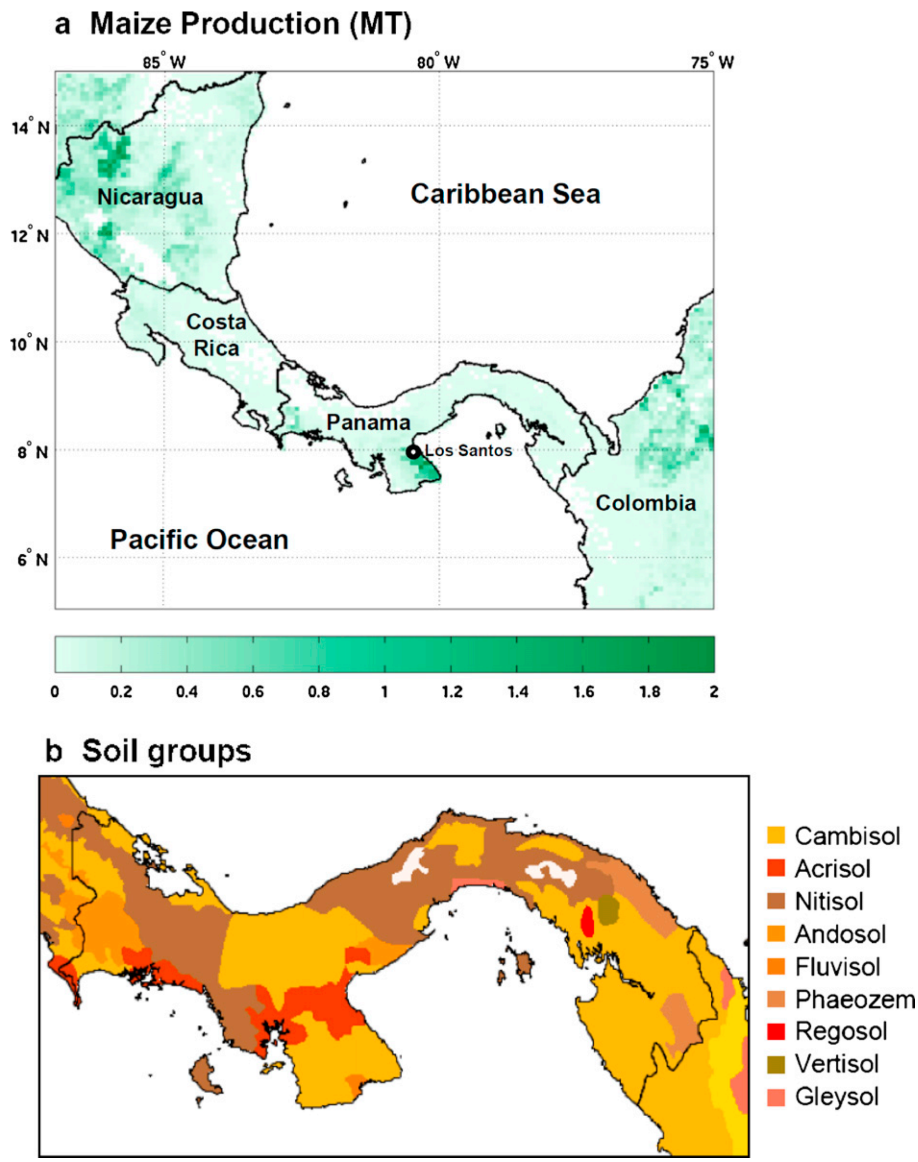

Fig. 1. (a) 2000 maize production estimates across Panama and surrounding vicinity (1000s of MT; from Monfreda et al., 2008). The location of the climate observations, Los Santos, is also noted at the neck of the Azuero Peninsula. (b) Harmonized World Soil Database soil groups for Panama (FAO, 2009).

the 1980–2009 climatology of temperature and rainfall for Los Santos, along with climate model projections described in Section 3.2 below. Panama's tropical climate is most strongly affected by the seasonal migration of the Inter-Tropical Convergence Zone, which brings rainclouds and cooler temperatures to the Azuero Peninsula from late April into early December. July often brings a relatively drier spell known as the *veranillo*, followed by the wettest time of year in September and October. Two growing seasons are therefore possible: one before, and one after, the *veranillo* (referred to in Panama as *primera coa*, or "first planting", and *segunda coa*, or "second planting", respectively).

Farmers in Panama cultivate a wide variety of soils using varying seeds, practices, and amendments. CERES-Maize was calibrated for Los Santos and the Azuero Peninsula agricultural region primarily from data contained in a report by the Panamanian Institute of Agricultural Investigation (IDIAP; Gordón, 2009). Although focused on more intensive rainfed cultivation with high fertilizer applications (130–200 kg N/ha) for the segunda coa season, Gordón et al. (2006) and Gordón (2009) provide planting dates, plant population, fertilizer application schedules, and data on phenology and yields for 10–25 cultivar trials over the 2001–2007 period.

The majority of maize cultivars grown in Panama come from the Pioneer brand. In the 1990s Pioneer X-304c made up ~75% of the planted crop (this cultivar was examined in Pérez et al., 1991; Camargo et al., 2002), followed by a short period in the early 2000s where cultivars like X-1358K replaced X-304c. Pioneer 30F-80 has made up ~80% of planted maize in the past 5 years. The Pioneer X-304c cultivar is included in DSSAT v4.5, and was modified according to the Gordón (2009) phenology and yield (which are common across cultivars in Azuero) to estimate the more current hybrids (Modified Pioneer X-304c B). Proper simulated flowering and maturity dates (55 and 115 days after planting, respectively), as well as closer yields, were achieved by reducing the thermal time between emergence and the end of the juvenile phase (cultivar parameter *P1* in CERES-Maize), lengthening the thermal time from silking to maturity (*P5*), and increasing the maximum number of kernels per plant (*G2*).

Table 1 describes the calibrated configuration, and the next section describes the performance of this configuration against

Table 1
Agricultural options for CERES-Maize crop model run for weather series at Los Santos, Panama. As discussed in Section 5 and shown in Figs. 6 and 7, the range of variation for climate impacts, holding other selections at default, are also shown for the first six options.

Option	Calibrated selection	Range of variation tested for climate impacts	Notes
Season	Segunda coa	Primera coa and Segunda coa	Rainfall in this region initiates in the spring, breaks in mid-summer (called the *veranillo*), and is high in the autumn, allowing two growing seasons. The planting date representing the primera coa is May 15 (following Sacks et al., 2010).
Planting date	September 1	August 12, August 22, September 1, September 11, September 21	Calibrated plant date and plausible range for segunda coa growing season from Gordón et al. (2006), and Gordón (2009).
Fallow period	14 days	0, 7, 14, 21, 42, and 84 days	Provides soil moisture spin-up and resolution of early-season drought.
Soil profile	WI_CMPA011 (Ferralic Cambisol)	14 soil profiles in Panama (6 Cambisols, 2 Acrisols, 2 Andosols, 2 Luvisols, 1 Phaezoem, and 1 Gleysol)	From World Inventory of Soil Emission Potentials database (WISE; Batjes and Bridges, 1994). Calibrated for Cambisol according to Harmonized World Soil Database (HWSD; FAO, 2009) and baseline performance.
Cultivar	Modified Pioneer X-304c B	Pioneer X-304c, Modified Pioneer X-304c A, Modified Pioneer X-304c B Hybrid Obregon, and PB-8.	Pioneer X-304c historically common in Panama (Camargo et al., 2002; Pérez et al., 1991). Genetic coefficients for each included in DSSAT. Pioneer X-304c modifications speed up flowering date and increase grain size to match Gordón (2009).
Fertilizer applied	150 kg N/ha	0, 20, 50, 80, 100, 150, and 200 kg N/ha, as well as experiment with no N-stress permitted.	Although 150 kg N/ha is higher than commonly applied in Panama today (Gordón et al., 2006; Gordón, 2009), simulations are designed to resemble high-input yields in more developed future.
Soil moisture at initialization	75% of saturation throughout column		Initialization occurs at the beginning of the pre-sowing fallow period. The actual soil moisture at planting depends on this initialization and the fallow period spin-up.
Irrigation	None (rainfed)		As is common in Panama.
Plant population	6 plants/m^2		Gordón (2009). Plant populations were ∼5.33 plants/m^2 in the 1990s and have risen to 6–6.8 plants/m^2 today.

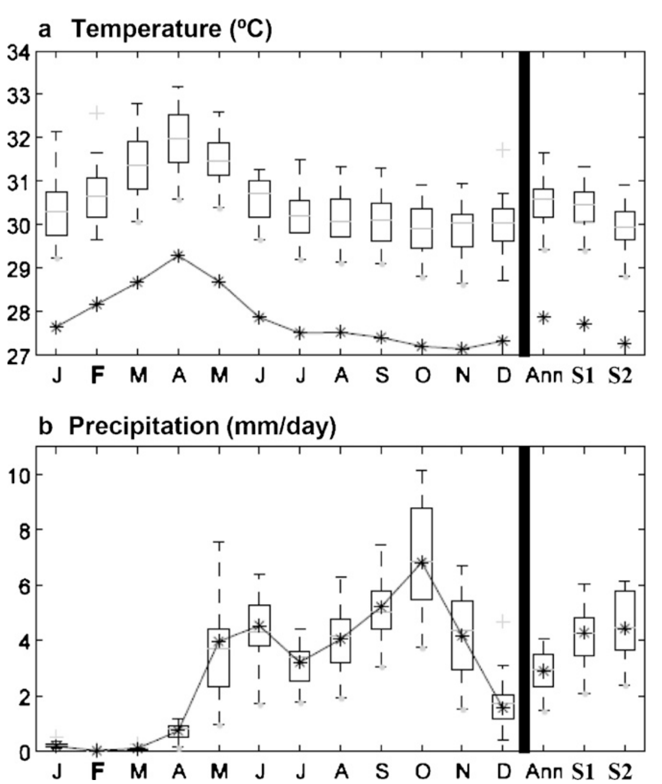

Fig. 2. Baseline (black line and stars) and A2 End-of-Century projected range (across 16 GCMs) of monthly, annual, and seasonal a) temperature and b) precipitation for Los Santos, Panama. S1:primera coa: May–August; S2: segunda coa: September–December.

observations. Table 1 also presents the parameter variations tested in the sensitivity exercises examining the effects of management options and climate change conditions described in Section 5 below. These include an intermediate hybrid (Modified Pioneer X-304c A) with thermal times and kernel numbers in between the calibrated Modified Pioneer X-304c B and original Pioneer X-304c in order to better understand the cultivar adjustments.

3. Calculation

3.1. Crop model performance and reported yields

Fig. 3 presents a comparison between the calibrated crop model simulations, cultivar trials reported in Gordón (2009), and annual national maize production reported for Panama by the United States Department of Agriculture Foreign Agricultural Service (USDA FAS; available at http://www.fas.usda.gov/psdonline, last accessed June 30th, 2011). As the CERES-Maize configuration was calibrated against mean observed phenology, common management practices, and representative soils, seasonal correlations with observed yield are independent of the calibration procedure. Over the 2001–2007 period, the calibrated segunda coa season simulations track the mean of the cultivar trials with a correlation coefficient of +0.92 (significant at 0.001 level). Individual cultivar trials also exhibit the higher variability of the calibrated simulations. Although low in comparison to the cultivar trials reported in Gordón et al. (2006) and Gordón (2009), the calibrated simulations' fertilizer levels (150 kg N/ha in three applications) and yields are higher than most Panamanian farms and should therefore be considered high-input yields for the region. Over the 1980-2009 period, the calibrated segunda coa season simulated yields have a mean of 5848 kg/ha and follow USDA FAS Panamanian

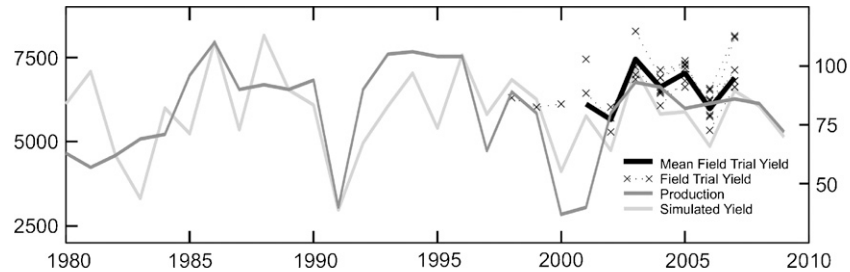

Fig. 3. 1980–2009 yield diagnostics. Baseline yields (kg/ha) simulated under the calibrated configuration are shown in light gray and compared to mean field trial data (black) drawn from Gordón (2009; with ×'s representing individual and linked multi-year field trials) and Panamanian maize production (1000s of MT; dark gray, from USDA Foreign Agricultural Service.

maize production with a correlation coefficient of +0.55 (significant at 0.01 level), underscoring the considerable contribution of the Azuero Peninsula's segunda coa maize season to national production and establishing the calibrated CERES-Maize configuration as a useful model for Panama. Among the 14 Panamanian soils in the WISE database, the calibrated soil profile (WI_CMPA011; Ferralic Cambisol) and the segunda coa season compared best against both the cultivar trials and national production despite being relatively shallow and prone to water stress.

The relationship between maize yields and key climate metrics is explored in Fig. 4. As expected, simulated yields generally show larger absolute correlations to Los Santos data than the national production numbers that are averaged across a wider variety of areas and farming systems, but both metrics of maize production generally agree on the indicative climate metrics. Simulated yields and reported national production are both negatively correlated with a warm segunda coa growing season (here defined as September–December) that accelerate development and increase evapotranspiration rates (Fig. 4a). The strongest climate signal is a positive correlation between agricultural production and growing season rainfall, indicating that water stress is the primary obstacle to higher and more consistent yields (Fig. 4b; see also Gordón et al., 2004b). Maize also appears to favor a higher number of growing season rain days, likely due to the likelihood of more net rainfall but also to a reduction in dry spells that cause water stress and a reduction in nitrogen leaching and runoff in comparison to seasons with equal total rainfall coming in fewer, more intense storms (Fig. 4c). Finally, higher standard deviations of growing season temperature correlate weakly with reduced simulated yields, suggesting a positive crop response to more consistent temperatures (Fig. 4d). The impacts of higher frequency metrics are worth exploring as future studies examine the effects of climate change on sub-seasonal temperature and rainfall variability.

3.2. Climate scenarios

The primary tools for investigating large-scale climate changes are the general circulation models (GCMs) developed at modeling centers around the world and contributed to the Third Coupled Model Intercomparison Project (CMIP3; Meehl et al., 2007) for analysis informing the Intergovernmental Panel on Climate Change's 4th Assessment Report (IPCC AR4; Solomon et al., 2007; Parry et al., 2007). These models are built on resolved physical dynamics as well as a set of statistical parameterizations that represent unresolved processes, and have been calibrated by large-scale climate observations and more detailed studies of complex processes. The models work as a holistic system where it is difficult to trace uncertainty back to particular biases, but the range of projected outcomes acts to integrate these discrepancies into a model-based uncertainty that can be thought of as a subsample of the actual (but unknown) probability distribution of climate sensitivity to greenhouse gases and other radiatively important agents. It is possible that particular biases will be common to all GCMs, particularly in areas like Mesoamerica where coarse model resolution cannot resolve complex mountains and coastlines, but the Azuero Peninsula is near sea level (Los Santos is at 16 m elevation) and has a largely maritime climate consistent with the larger GCM scale. To examine uncertainty owing to societal pathways, we analyze future simulations from two emissions scenarios (SRES, 2000) – the A2 (higher emissions) and B1 (lower emissions growth). Outputs for these emissions scenarios for 16 GCMs (see Table 2) were available at the CMIP3 archive at the Program for Climate Model Diagnosis and Intercomparison (PCMDI).

Future climate scenarios for Los Santos were produced using the "Delta Method" (Gleick, 1986; Arnell, 1996; Wilby et al., 2004) that adjusts daily historical observations to match mean monthly climate changes as determined by GCM simulations. Using AgMIP's time slice conventions, climate change factors for temperature and precipitation were calculated by comparing the "Near-Term" (2005–2034), "Mid-Century" (2040–2069), and "End-of-Century" (2070–2099) future simulation from each GCM/emissions scenario to the same model's 1980–2009 20th century simulation[2] for the grid box corresponding to Los Santos, Panama. These comparisons remove much of the inherent biases in each GCM, reduce the noise produced by interannual modes of variability, and focus on the climate changes that these models are designed to produce. This approach is built upon long-term changes, so results are best interpreted on the 30-year climate timescale recommended by the WMO (WMO, 1989).

New scenarios were generated by imposing these monthly changes in temperature and percentage changes in precipitation on the filled Los Santos historical record, with [CO_2] fixed at the level corresponding to the midpoint of the 30-year time slice in the corresponding emissions scenario (Table 3). The result is 96 future scenarios (16 GCMs × 2 emissions scenarios × 3 future periods), each containing 30 years of daily meteorological values that were used to drive maize simulations. Each scenario's year-to-year variation and most day-to-day variations are largely identical to the baseline period scenario, as all values within a given month over the 30-year period are shifted using a common change value. There is also the potential for large changes in rainfall when a GCM's incorrect seasonal variation indicates a dry month when observations suggest rainier conditions, as small, chance absolute changes in simulated rainfall during this month could produce dramatic percentage changes in the associated scenario (as appears to be

[2] 2000–2009 drawn from B1 emisssions scenario, as 20th century simulations end in 2000. There is very little difference between emissions scenarios in the first decade.

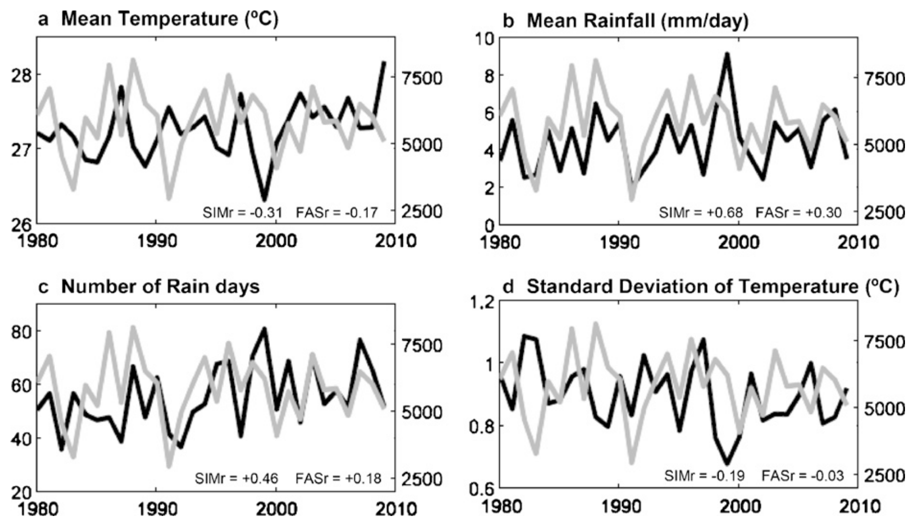

Fig. 4. 1980–2009 evaluation of calibrated yield simulations (kg/ha; gray) and the growing season (a) mean temperature; (b) mean rainfall; (c) number of rain days; and (d) standard deviation of temperature. The correlation coefficient of the climate metric and simulated yields (SIMr) and Panamanian production from the USDA FAS (FASr) are also shown.

Table 2
CMIP3 general circulation models analyzed (from the PCMDI), along with their hosting center, approximate grid box resolution, and the equilibrium climate sensitivities of each model's atmospheric component to an instantaneous doubling of carbon dioxide relative to preindustrial levels (based upon Randall et al., 2007).

GCM	Institution	Atmospheric resolution (lat × lon;°)	Climate sensitivity (°C)
bccr_bcm2.0	Bjerknes Center for Climate Research, Norway	1.9 × 1.9	Not reported
Cccma_cgcm3.1(T63)	Canadian Center for Climate Modeling and Analysis, Canada	1.9 × 1.9	3.4
cnrm_cm3	CERFACS, Center National Weather Research, METEO-FRANCE, France	1.9 × 1.9	Not reported
csiro_mk3.0	CSIRO Atmospheric Research, Australia	1.9 × 1.9	3.1
gfdl_cm2.0	Geophysical Fluid Dynamics Laboratory, USA	2 × 2.5	2.9
gfdl_cm2.1	Geophysical Fluid Dynamics Laboratory, USA	2 × 2.5	3.4
giss_model_er	NASA Goddard Institute for Space Studies, USA	4 × 5	2.7
Inmcm3.0	Institute for Numerical Mathematics, Russia	4 × 5	2.1
ipsl_cm4	Insitut Pierre Simon Laplace, France	2.5 × 3.75	4.4
miroc3.2 (medium resolution)	Center for Climate System Research; National Institute for Environmental Studies; Frontier Research Center for Global Change, Japan	2.8 × 2.8	4.0
miub_echo_g	Meteorological Institute of the University of Bonn, Germany	3.9 × 3.9	3.2
mri_cgcm2.3.2a	Meteorological Research Institute, Japan	2.8 × 2.8	3.2
mpi_echam5	Max Planck Institute for Meteorology, Germany	1.9 × 1.9	3.4
ncar_pcm1	National Center for Atmospheric Research, USA	2.8 × 2.8	2.1
ncar_ccsm3.0	National Center for Atmospheric Research, USA	1.4 × 1.4	2.7
ukmo_hadcm3	Hadley Center for Climate Prediction, Met Office, UK	2.5 × 3.75	3.3

the case for one outlying model in the A2 Near-Term Scenario, see Section 5.3).

This pilot study seeks to gauge the level of uncertainty owing from the suite of GCMs and emissions scenarios and compare it to uncertainties in the impacts assessment related to farm-level information, so a simple delta approach is sufficient. More complex scenario generations would allow for changes in rainfall frequency, extreme behaviors, natural modes of variability (such as the El Niño/Southern Oscillation that has a strong effect on Central America), and finer-scale patterns of climate change that may be determined by complex mountains and coastlines (examined with a regional climate model, for example). Investigations using these more complex approaches for Mesoamerica are ongoing, and methodological uncertainty will also be a focus of AgMIP.

Fig. 2 shows the temperature and precipitation ranges across the 16 scenarios based upon A2 End-of-Century GCMs. A substantial warming is evident in all GCMs, as expected. The sign and magnitude of precipitation changes are unclear, however, with median rainfall totals matching the baseline to a remarkable degree.

Table 3
Carbon dioxide concentrations for each simulation period (SRES, 2000), as well as the median (across GCMs) of 30-year mean yield change in default simulation compared to the baseline period (5848 kg/ha).

Scenario	Time period	$[CO_2]$[a]	Median yield change[b]
Baseline	1980–2009	360 ppm	–
A2 Near-Term	2005–2034	417 ppm	−0.5%
B1 Near-Term	2005–2034	412 ppm	−0.1%
A2 Mid-Century	2040–2069	556 ppm	+2.4%
B1 Mid-Century	2040–2069	496 ppm	−0.8%
A2 End-of-Century	2070–2099	734 ppm	+4.5%
B1 End-of-Century	2070–2099	541 ppm	+1.5%

[a] CO_2 concentrations for entire 30-year period set at central year's value.
[b] Median (across 16 GCMs) 30-year mean yield change in comparison to baseline period.

4. Future yield simulations

Fig. 5 shows 30 simulated years from each GCM for the A2 and B1 scenarios' Near-Term, Mid-Century, and End-of-Century periods

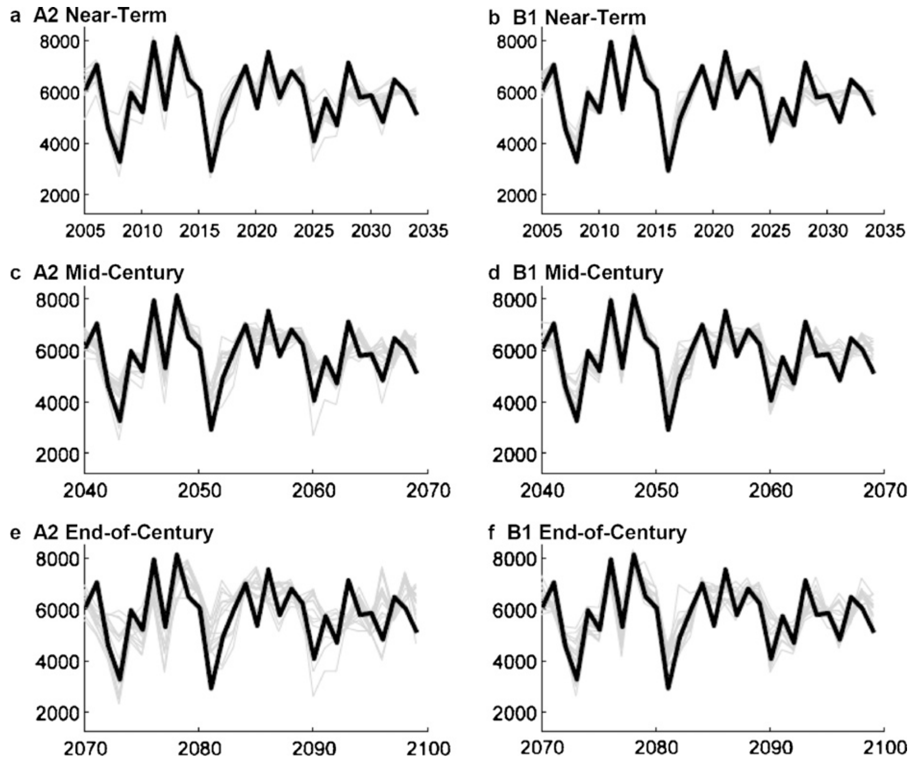

Fig. 5. Simulated yields (kg/ha) from scenarios of future climate projections. Simulated 1980–2009 baseline yields are shown in black, and scenarios based upon the 16 GCMs are shown as gray lines. (a) A2 Near-Term; (b) B1 Near-Term; (c) A2 Mid-Century; (d) B1 Mid-Century; (e) A2 End-of-Century; (f) B1 End-of-Century.

with the baseline yields for reference. The median (across 16 GCMs) 30-year mean yield changes for each panel are noted in Table 3. Because future scenarios contain the same interannual sequence as the baseline period, each simulation has a similar 30-year pattern.

Simulations of the Near-Term A2 and B1 scenarios produce median yield losses of 0.5% and 0.1% compared to the baseline period, respectively, which would hardly be noticed among the larger seasonal variation. In the 25 years that differentiate the 1980–2009 and the 2005–2034 Near-Term period, most GCMs project only moderate warming and modest changes in precipitation (some wetter, some drier), however [CO_2] increases by ~15% and keeps mean yields relatively steady. Simulations of the Mid-Century A2 scenario produce median yield increases of 2.4% compared to the baseline period, while the B1 scenario produces median yield losses of 0.8%.

End-of-Century simulations produce median yield gains for both scenarios, with the A2 and B1 increasing by 4.5% and 1.5% over the baseline, respectively. To understand the processes that lead to these yield gains it is instructive to note that seasonal yields do not increase uniformly across the 30-year simulation. The A2 End-of-Century simulations actually show declines in the highest-yielding seasons (years 2, 7, 9, 17, and 24 in Fig. 5e), but also dramatically reduce the incidence of low-yielding seasons (years 4, 12, and 21). This improvement of low-yielding seasons is actually a side-effect of the accelerated physiological development of maize under warmer temperatures, which causes maturity a full 10 days earlier in the A2 End-of-Century simulations than in the baseline period. While the low-yielding baseline seasons were greatly affected by an early end of the rainy season in late November or early December and high water stress during the crucial grain-filling phase, crops maturing 10 days earlier find substantially higher soil moisture and are less stressed. High-yielding seasons experience much less water stress, and therefore only experience yield decreases from this accelerated maturation. In sum, accelerated maturity and the climatology of Panama's post-*veranillo* growing season lead to mean yield increases and higher yield consistency – both encouraging aspects of these simulation results – but considerable uncertainty is apparent among GCM scenarios.

5. Uncertainty in baseline yield and yield change projections

Maize is grown in Panama under diverse conditions and it is likely that very few (if any) farms follow the exact specifications of the calibrated configuration. Other farms may grow maize during the pre-*veranillo* (primera coa) growing season, use a different planting date, feature a distinct soil profile, sow a separate maize cultivar, and/or apply more or less fertilizer, among other factors. Can a farmer with a unique farming system gain any insight from the calibrated simulations presented above, or must research instead start from scratch and calibrate the model for each specific situation? While it is not practical to cater to each individual farm, the following section examines the extent to which a specific simulation configuration (including model-based options such as the length of the simulated fallow period before planting to determine initial soil moisture) may typify climate impacts on a broader region. To explore these options we present the sensitivity of maize yield to farm-level information and management decisions during the baseline period (Fig. 6) as well as under future climate scenarios (Fig. 7), and compare these changes to uncertainties related to different aspects of climate change (Figs. 8 and 9). Each 30-year sensitivity test is identical to the calibrated configuration of CERES-Maize (as described in Table 1) except for the option in question in order to demonstrate the crucial sources of uncertainty in the impacts assessment. Absolute yields from these sensitivity studies may also be used as an exploration of adaptation options that may help prioritize field trials in coming years, but yield changes

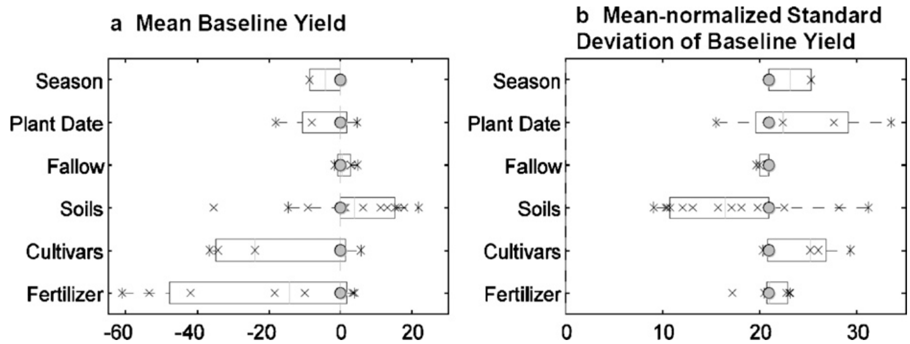

Fig. 6. Sensitivity of simulated (a) mean baseline yield (as percentage of mean calibrated yield = 5848 kg/ha) and (b) standard deviation (as % of the experiment's mean) of baseline yield to farm-level information and management decisions during the baseline period, including growing season, planting date, length of the simulated fallow period, soil profile, cultivar, and the amount of fertilizer added. ×'s represent each sensitivity test, and gray circles represent the calibrated configuration (see Table 3 for calibrated configuration and options tested).

(rather than absolute yields) are the primary focus of the future results presented here.

5.1. Sensitivity of baseline yield to farm-level options

In addition to segunda coa maize, the calibrated simulation was also run for primera coa maize planted on May 15th (following Sacks et al., 2010). Simulated primera coa maize has 8.7% lower mean yield than segunda coa maize during the baseline period (Fig. 6a), and is also less consistent (primera coa maize's standard deviation of yields, as a percentage of its mean yields, is 25.2%, as opposed to 20.9% for segunda coa maize; Fig. 6b). Both quantities suggest that a higher reliability on the segunda coa season is merited.

Five planting date tests (spanning the 41 days centered on the calibrated date, September 1st) have mean yields ranging from 4.6% above to 18.2% below the calibrated simulation. Planting is set to occur regardless of field conditions to enable this comparison, however in reality soil saturation can delay planting and lead to yield losses from end-of-season dry conditions (as occurred in the 2010 season). The highest baseline yields come from planting August 22nd, which helps complete the grain-filling stage before acute water stress in early December, similar to the benefits of accelerated maturity in the future scenarios discussed in Section 4 above. The latest planting date (September 21st) has the lowest and least consistent yields (its inter-annual standard deviation of yields is 33.5% of its mean yield), as rains ended too early and crops were forced to complete their development under severe water stresses.

Simulations using six fallow period lengths allowed the model more or less time to spin up the soil moisture before planting, testing the robustness of the calibrated configuration and the initialization of soil moisture at 75% of saturation throughout the profile. Mean baseline yields for fallow period lengths between 0 and 3 weeks hold within ±2% of the calibrated values, while mean-normalized standard deviations are within 0.2%. Longer fallow periods slightly increase means and reduce the mean-normalized standard deviation of yield, suggesting that true initial soil conditions in the middle of the rainy season are actually slightly more favorable than the calibrated configuration assumes.

The selection of a soil profile from the 14 WISE soil profiles identified as being in Panama showed a substantial impact on baseline yield. The soil with the highest and most consistent baseline yields is a 180 cm-deep Andosol, which may be characteristic of the Chiriqui maize-growing region in Western Panama (recall Fig. 1b). A shallow Andosol has a similarly productive baseline

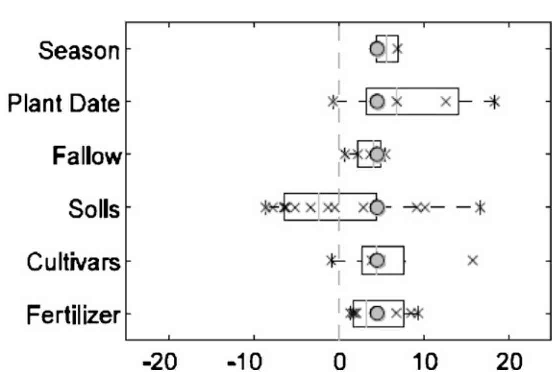

Fig. 7. Sensitivity of median (across 16 GCMs) simulated mean yield changes (%) for the A2 End-of-Century simulation in comparison to baseline yields (5458 kg/ha), as in Fig. 6. Gray circles represent the percentage change (+4.5%) of the calibrated configuration.

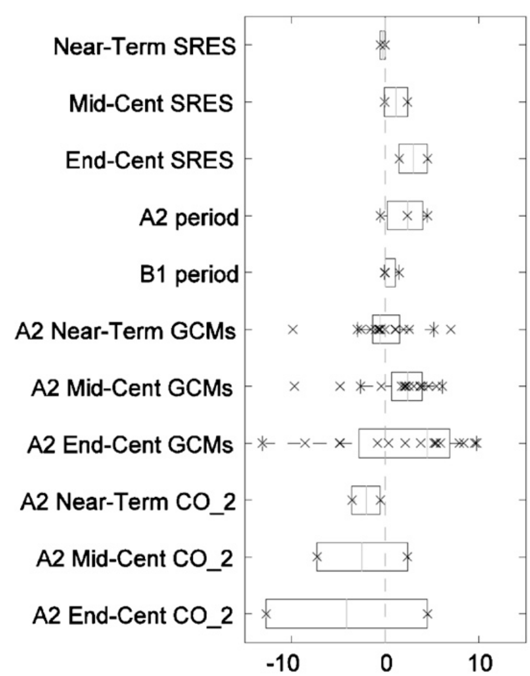

Fig. 8. Sensitivity of simulated mean yield changes (%) to climate uncertainties in comparison to baseline yields (5458 kg/ha). Uncertainties include the selection of emissions scenario for each of the three future periods, the A2 and B1 emissions scenarios across all three future periods, the range of GCMs for the A2 scenario for each of the three future periods, and the effect of simulations with and without [CO_2] effects for each of the three future periods. All experiments are presented as the median (across 16 GCMs) mean yield change with the exception of the GCM lines that are presented as simply the mean yield change across the 30 year GCM scenario.

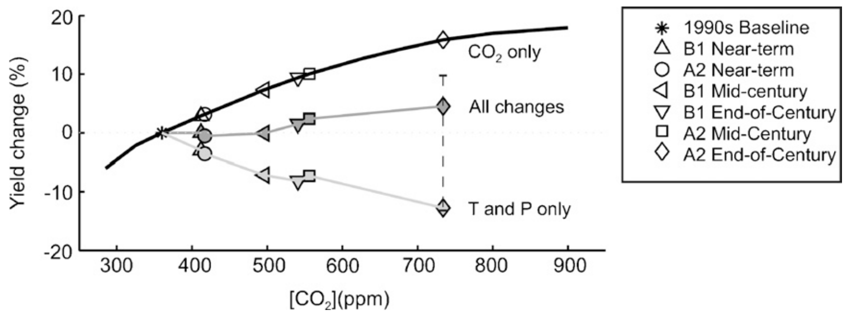

Fig. 9. Sensitivity of mean yield changes to [CO_2]. The black line represents mean yields from baseline climate run under various [CO_2], the light gray line displays mean yields from all future climate change scenarios based upon elevated [CO_2] concentrations but where crop model simulations held [CO_2] at baseline concentrations, and the dark gray line shows the median of simulations performed with all climate changes. The error bar shows the range of GCM mean yield changes for the A2 End-of-Century simulation to facilitate comparison with Figs. 6–8.

period. The lowest and least consistent yields are the Phaeozem profile characteristic of the Eastern Caribbean coast, an area with little maize production today. Yields from the other soil profiles do not otherwise show strong correlations with depth or soil classification. CERES-Maize applications to reproduce rain-fed yield must therefore recognize its high sensitivity to Panama's diverse soils, particularly if the goal is to aggregate results to match country-level production.

Five maize cultivar tests reveal that only Hybrid Obregon produces higher (5%) yields than the calibrated cultivar (Modified Pioneer X-304c B). Hybrid Obregon features very rapid maturation and extremely high kernel counts, which suits the water-stressed environment nicely. The Modified Pioneer X-304c A and Pioneer X-304c are 23.8% and 36.6%, respectively, below the calibrated cultivar due to longer emergence-juvenile phase maturation and reduced kernel numbers, while PB-8 is 34.2% below the calibrated cultivar due to dramatically lower kernel numbers. Large mean yield range among cultivars suggests that CERES-Maize applications benefit greatly from more accurate cultivar traits.

Tests with six fertilizer amounts demonstrate a strong sensitivity of baseline yields to nitrogen stresses. An additional experiment was conducted where nitrogen stress was not permitted. Mean baseline yield increases with additional fertilizer applications and reduced nitrogen stresses, as does yield consistency above 50 kg N/ha. The 0 kg N/ha simulation produced mean yields more than 60% below the calibrated (150 kg N/ha) simulation, while the 200 kg N/ha experiment produced nearly the same yields as the Nitrogen-stress-free simulation (3.4% and 3.8% above the calibrated simulation, respectively), suggesting strongly diminished returns for fertilizers applications beyond 150 kg N/ha. These results agree with field experiments in Panama that revealed a quadratic rise in yield followed by a plateau above 147 kg N/ha (Gordón et al., 2004a).[3] The Nitrogen-stress-free simulation produces a dramatic improvement in the mean-normalized standard deviation of yield, however.

5.2. Sensitivity of yield changes to farm-level options

Baseline yields show substantial sensitivities to farm-level options, but these sensitivities do not necessarily translate into large sensitivities when investigating the effect of climate changes on the field in question. This section examines the potential to generalize across farming systems by assuming that the percentage yield change caused by climate change in the calibrated simulation may be more universal than the absolute yields. In this way we investigate whether model biases in the baseline configuration may be independent from the effects of climate change impacts in an approach that is analogous to the climate scenario's Delta Method. This section (and Fig. 7) focuses on the A2 End-of-Century simulation because the sensitivities' signals are more clearly demonstrated under more dramatic climate changes.

A2 scenario maize yields are projected to increase more rapidly between now and the End-of-Century period during the primera coa season (+6.9%) than the segunda coa season (+4.5%). Segunda coa maize, which has higher yields in the baseline, continues to exceed the primera coa season in absolute yield by 7% in this future scenario, however.

Maize's accelerated maturation under warmer conditions has a dramatic effect on late-planted segunda coa maize, with the largest percentage yield gains found in maize planted September 21st (+18.4%) as grain-filling water stress is more frequently avoided. In contrast, the most productive baseline plant date (August 22nd, which rarely experienced late-season water stress) shows negative yield changes (−0.7%). The calibrated September 1st planting date has the highest absolute yield among all planting dates in the A2 End-of-Century simulations, with values very similar to the baseline August 22nd planting due a similar timing for the accelerated grain-filling period. The difference in yields between early and late planting dates in the segunda coa is substantially decreased, suggesting more favorable conditions for dual-season maize cultivation as there is projected to be more time between the primera coa season harvest and the end of the productive segunda coa sowing window.

Projected yield changes were not very sensitive to the simulated length of the fallow period before planting. The lowest yield changes (+0.8%) occurred for the simulations where the soil profile was initiated at 75% of saturation 7 weeks before the planting date, while the highest yield changes (+5.5%) were initiated on the day of planting. Simulations where shorter fallow periods lead to higher water stress (recall Section 5.1) see a higher benefit from improved water retention under higher [CO_2], but projected climate impacts on maize yield fall in a relatively tight range regardless of the fallow period.

Climate impact responses for all soil profiles, the selection of which accounts for large deviations in mean baseline yield (from −35.4% to +21.8% in comparison to the calibrated soil), result in an envelope of mean yield changes between −8.6% and +16.7% gains. Although still substantial, the soil profile uncertainties of climate impacts are greatly reduced in comparison to the baseline soil profile uncertainties. Baseline yields and future changes display a strong negative correlation (−0.96; significant at 0.001 level), however, meaning soil profiles that produce higher mean baseline yields are more negatively affected by climate changes. As

[3] 147 kg N/ha was the median threshold among field experiments, with some locations showing higher and lower sensitivities (see Gordón et al., 2004a, for more details).

baseline yields are strongly limited by water stresses, these simulations suggest that adaptations alleviating water stress increase overall yields but reduce the water-holding benefits of elevated [CO_2] and accelerated maturity, leading to declining yields as the detrimental effects of higher temperatures are more evident.

The selection of maize cultivar alters baseline mean yields by nearly 40%, but has a smaller but still substantial impact on future yield changes. Pioneer X-304c shows the highest yield gain (+15.8%), but its absolute yield still falls well below the calibrated cultivar. Hybrid Obregon (+3.9%) shows a similar yield gain to the calibrated variety (+4.5%), maintaining its edge in mean yield. Only PB-8 shows a negative yield change (−0.9%). No clear mechanism links a cultivar's mean baseline yield to its yield changes under future climate scenarios, so cultivar calibration remains a significant challenge to understanding climate impacts.

Fertilizer amounts affect baseline mean yields by up to 60% but have a more modest impact on yield changes for the A2 End-of-Century. Farming systems with low fertilizer amounts (0 and 20 kg N/ha) only show slight yield gains (1.7% and 1.4%, respectively). Moderate fertilizer systems (50, 80, and 100 kg N/ha) produce the highest percentage yield gains (6.8%, 9.4%, and 8.5%), while the highly fertilized systems (150 and 200 kg N/ha or no N-stress simulation) produce lower yield gains (4.5%, 1.9%, and 2% respectively). Thus, the added yield benefit from applying more than 100 kg N/ha diminishes in the future scenario.

5.3. Sensitivity of yield changes to aspects of climate variability and change

The first three lines in Fig. 8 show the median (across 16 GCMs) 30-year mean yield changes for the A2 and B1 scenarios in each future time period. Their difference demonstrates the potential impact of global greenhouse gases mitigation efforts, which will determine the emissions scenario that comes to fruition. The Near-Term A2 (−0.5%) and B1 (0.0%) scenario yield changes suggest that differing emissions trajectories are not very important to changes in maize yield for the next few decades. Societal emissions pathways begin to distinguish themselves in the Mid-Century, with A2 yields trending upwards (+2.4%) while B1 yields hold steady (−0.1%). By End-of-Century the median of both A2 and B1 simulations have increased yields (+4.5% and +1.5%, respectively). The next two lines show these results in a different way, demonstrating how A2 yields increase more rapidly with time while the B1 increase is slower. Sensitivity to time period also reflects the uncertainty that real changes could arrive sooner or later than projected depending on the accuracy of each GCM's climate sensitivity.

These small median yield changes mask a much larger uncertainty, however. Lines 6–8 of Fig. 8 show the 30-year mean results from scenarios based upon each of the 16 A2 GCMs for the future time periods, revealing considerable range in yield changes depending on model uncertainty. It is clear that reliance on a single model would have been problematic, as even in the Near-Term there are considerable outliers (one GCM had warm temperatures and pessimistic declines in autumn rainfall, while another optimistically projected future cooling for September and October). In general the clusters of GCM results follow the medians toward increasing yields as the future progresses, however their inter-quartile ranges increase from 2.8% in the Near-Term to 3.2% in the Mid-Century and then 9.7% for the End-of-Century, a spread that often exceeds the median yield changes and leaves Panamanian stakeholders with difficult risk assessments. The 4 A2 End-of-Century GCM scenarios with the lowest projected rainfall over the segunda coa growing season all project yield declines, suggesting that there is still considerable need for improved climate model projections to tighten the uncertainty in this region. More consistent rainfall projections would have a direct impact on stakeholder confidence in taking action to ensure economic and food security.

Even in the most extreme cases described above, projected mean yield changes remain small in comparison to interannual variability of maize yield. In the baseline calibrated simulation (only 30 years; recall Fig. 3), high and low years produced yields nearly 50% below and 40% above the mean, suggesting that the impacts of climate change on Panamanian maize yields will be difficult to separate from ongoing seasonal variability unless long-term averages are compared. The characteristics of interannual variability are also likely to change and may have a particularly strong influence on extreme growing seasons. These uncertain changes (which are the subject of an ongoing study) were not captured by the delta approach to scenario generation used in this study. Of course, changes in population, demographics, adaptation, and water supply will also obscure the climate changes isolated in this impacts assessment.

5.4. Sensitivity of maize yield to CO_2 concentrations

The final three rows in Fig. 8 show the projected yield changes from simulations of the future periods with, and without, [CO_2] impacts. Elevated [CO_2] is widely known to affect agricultural production (Easterling et al., 2007; Hatfield et al., 2008), however the extent that the growth of any given crop is affected is the subject of considerable debate (Long et al., 2006; Tubiello et al., 2007a,b; Ainsworth et al., 2008; Challinor and Wheeler, 2008; Kimball, 2010) and ongoing research in field, chamber, and modeling experiments (CCSP, 2008; Fleischer et al., 2010; Kimball, 2010; Boote et al., 2010; White et al., 2011). Boote et al. (2010) recognize that crop models often rely on [CO_2] sensitivity experiments that are now more than 20 years old (particularly to model the less-sensitive C_4 crops like maize), and that fewer [CO_2] response trials have been conducted under diverse climates outside of major mid-latitude agricultural areas. Challinor and Wheeler (2008) note that, for C_3 crops under high [CO_2], the water-retention benefits from partial stomatal closure during dry periods may be offset by higher transpiration from increased leaf area. White et al. (2011), note that few crop models clearly include the detrimental effects of increased canopy temperatures with elevated [CO_2]. These effects are not reproduced by CERES-Maize. In conducting this study an additional uncertainty was also identified whereby projected impacts are substantially sensitive to differing model versions. The CERES-Maize version included in DSSAT v4.5.0.0.030 used in early comparisons has a much stronger response to elevated [CO_2] than the DSSAT v4.5.0.047 version used here, which has seen updates to soil evaporation routines and CO_2-response functions (following Hatfield et al., 2008). Despite these improvements, the considerable debate over whether or not the crop model [CO_2] enhancements are accurate will remain until more definitive results from field trials are incorporated.

Fig. 9 displays the results from a range of sensitivity tests designed to bound [CO_2] uncertainties in CERES-Maize. The black line and open symbols show mean yields from experiments that are identical to the calibrated baseline simulations except that the [CO_2] is set to correspond to A2 and B1 projections of the Near-Term, Mid-Century, and End-of-Century (see Table 3), as well as a pre-industrial level (285 ppm) and several additional values (325, 625, 675, 800 m and 900 ppm) to fill in and extend the yield response curve. The *x*-axis ([CO_2]) acts as a proxy for time as emissions rise, although the small kink apparent between the B1 End-of-Century simulations and the A2 Mid-Century simulations reflects the limitations of this proxy as climate reacts differently to the pace of changes in [CO_2] over these unequal periods. Absent

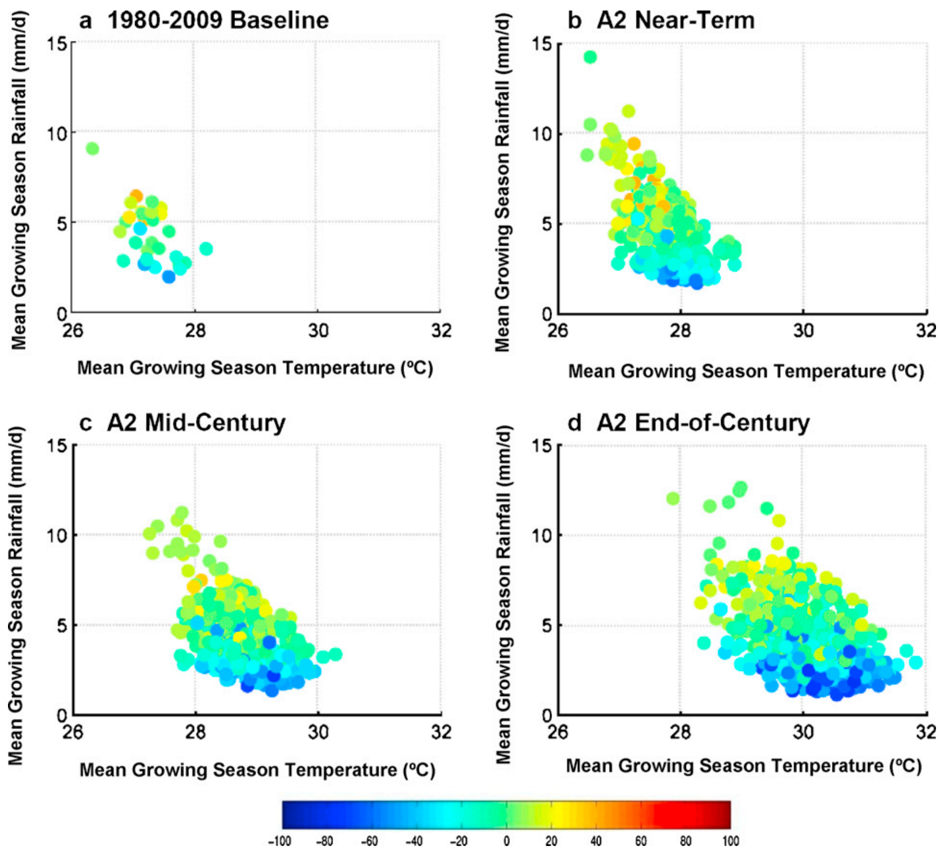

Fig. 10. Bivariate yield change responses for mean growing season temperature and rainfall under baseline [CO_2] for the (a) 1980–2009 baseline; (b) A2 Near-Term; (c) A2 Mid-Century, and (d) A2 End-of-Century. Each dot represents a particular season's yield as a percentage of the mean calibrated baseline yield.

other stresses, maize (as a C_4 crop) is expected to have a moderately favorable response (in comparison to the more sensitive C_3 crops) to elevated [CO_2] due to increased primary productivity, and the response for all species should eventually flatten out in a sign of diminishing returns (Kimball, 2010). This pattern is reflected in the calibrated simulations, however the presence of water stress allows for additional benefits under elevated [CO_2] as more efficient gas exchanges allow more efficient stomatal closure that reduces transpiration during droughts (Kimball, 2010).

The light gray line and symbols are the median (among 16 GCMs) of the 30-year mean yields simulated for each emission scenario and time period, however for these experiments [CO_2] was held constant at 1995 levels (360 ppm). These results show the impacts of projected changes in temperature and rainfall without any field-level [CO_2] effects. Considering the ongoing debate over the magnitude of [CO_2] yield impacts, if we assume that the positive effects of [CO_2] are overestimated by this version of CERES-Maize but are non-zero, the gap between the constant [CO_2] (light gray) line and the constant climate (black) line indicates the increasing importance of realistic simulations of [CO_2] sensitivity as projections for this region extend further into the future. Simulations with both climate and [CO_2] changes (dark gray line and symbols) are higher than the average of the CO_2-only (black) and no-CO_2-effect (light gray) simulations due to increased water retention capabilities in elevated-CO_2 scenarios with decreased rainfall. To place these changes in the context of errors discussed in the previous section, the error bar attached to the A2 End-of-Century simulation shows the range of 16 GCMs' mean yield changes with full climate and [CO_2] changes.

6. Uncertainties in bivariate yield response surfaces

Uncertainty introduced by GCM projections reflects the state of agreement across models, but it is possible that future conditions fall outside of this projected range and each new climate simulation requires a costly new impacts assessment. An alternative approach would be to use crop models to simulate yield responses to a broader range of climate states, capturing a wider uncertainty space and statistically fitting yield response emulators that could rapidly assess the impacts of new climate projections for integrated assessment models or other applications. By regressing yield changes against only two climate change variables, bivariate yield response emulators may provide a clear visualization to end-users and give a first estimate of yield changes for newly projected climate states.

Simple yield emulators are commonly based upon annual mean temperature and rainfall amounts, as these metrics are widely available and familiar to stakeholders. For crops in some regions, however, it is likely that alternative variables, temporal periods, and frequencies of variation may be more descriptive of yield variability. Underlying regressions may be based upon reported historical yields or simulations of complex impacts assessment models adjusted for different [CO_2], for example. In this study yield emulators are regressed against results from the baseline and all future climate scenarios (2910 simulated years in total) under [CO_2] held constant at 360 ppm (1995 levels). In order to identify important thresholds, AgMIP sensitivity tests will be designed to expand the uncertainty space for changes in temperature, precipitation, and [CO_2], as well as to

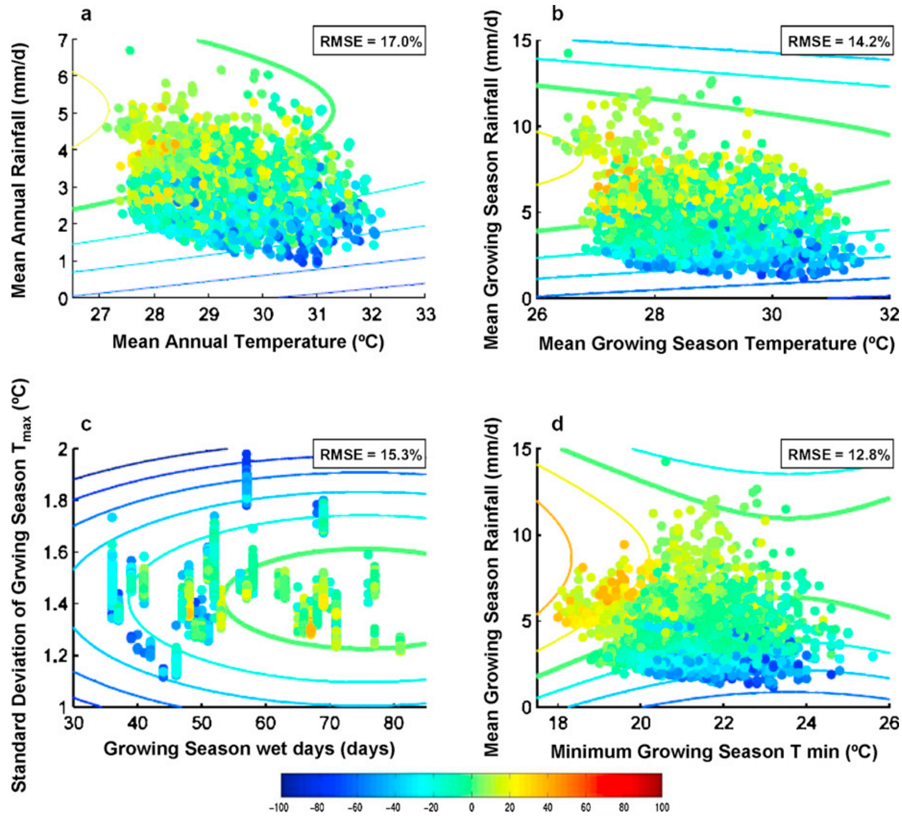

Fig. 11. Bivariate yield change response surfaces (as % of baseline mean yield) under baseline [CO_2] for: (a) mean annual temperature and rainfall; (b) mean growing season temperature and rainfall; (c) mean growing season rain days and the standard deviation of growing season daily maximum temperatures; and (d) minimum growing season daily minimum temperature and mean growing season rainfall.

investigate the importance of climate variability on seasonal production.

One advantage of bivariate yield responses is their appeal in visualizing climate and crop model uncertainties for end-users and stakeholders. Fig. 10 depicts the yield changes for all A2 simulations using Los Santos climate under baseline [CO_2] (360 ppm; all of the simulations from the light gray line in Fig. 9) according to mean growing season temperature and rainfall. Fig. 10a shows just the baseline years, which are tightly clustered around moderate rainfall and temperatures within a degree or so of 27.5 °C, although one outlying year is cooler and wetter (1999). For future periods all GCMs are displayed, demonstrating a progression toward warmer temperatures and an increasing spread in rainfall due to high GCM uncertainty. In the A2 Near-Term there are several cool and wet years with high yields (Fig. 10b), however future growing seasons are increasingly in the lower-yielding warm and dry quadrant. By the End-of-Century period it is extremely rare to be as cool as even the hottest baseline season. Drier scenarios produce substantial losses, while the wettest scenarios are showing diminishing returns and a reduction due to the high temperatures.

A lot of practical information may be gleaned from this type of bivariate analysis; however it is also clear that there are exceptions to the general bivariate response. For example, there are excellent years with slightly warmer conditions and only average rainfall while other seasons with similar conditions produce mediocre yields. Likewise, several cool and wet years have only average yields while similar conditions often create bumper crops. Before a statistical yield emulator may be trusted, it is important to determine how robustly various metrics predict yield responses.

Fig. 11 presents yield responses to four combinations of climate metrics with contours from the corresponding quadratic bivariate regression whereby yield Q is estimated using a least-squares fit to approximate coefficients a, b, c, d, and e according to climate metrics x and y:

$$Q = a + bx + cx^2 + dy + ey^2. \quad (1)$$

Fig. 11a shows the response to the annual mean temperature and rainfall, identifying precipitation as the more predictive factor although yield is more sensitive to high temperatures during wet times than under drought. High- and low-yield seasons with nearly identical annual mean temperatures of ~28 °C and rainfall of ~3 mm/day demonstrate that annual mean values are not sufficient to describe seasonal maize yields in Panama. When these variables are used as a seasonal yield emulator, Eq. (1) produces an RMSE of 17% versus the CERES-Maize simulated yields, which is likely not sufficient for practical application. Driven by mean annual rainfall and precipitation from 30-year scenarios, Eq. (1) can produce mean scenario yield changes with a Pearson's correlation of $r^2 = 0.85$. r^2 drops to 0.38 when the emulator is used to predict out-of-sample simulations with elevated [CO_2], however, suggesting that emulators based upon present-day conditions alone are not sufficient to predict future conditions with enough detail to achieve the accuracy needed for decision-making. As expected, using growing season temperature and rainfall instead of annual metrics improves emulator performance (Fig. 11b). It is also worth noting that growing season rainfall totals above 10 mm/day lead to predictions of lower yield as a result of nitrogen leaching. Without [CO_2] effects the seasonal emulator RMSE improves to 14.2%, with the 30-year scenario emulator producing $r^2 = 0.89$.

In addition to mean quantities, seasonal emulators based upon sub-seasonal metrics perform quite well. Fig. 11c shows the predictive ability of the standard deviation of growing season maximum temperatures and the number of growing season rain days, which produce a seasonal emulator with lower RMSE (15.3%) than the annual metrics. The importance of these variables was also reflected in the analysis of baseline climate sensitivities in Section 4 and Fig. 4, where the importance of regular rainfall events and stable temperatures were discussed. The delta scenarios examined here do not affect these metrics other than through rounding errors on large precipitation decreases or through differential monthly temperature changes, so they do not perform well in predicting future scenario yields in this study ($r^2 = 0.41$ without [CO_2] effects). In light of these results, the authors are utilizing ensembles of regional climate models in ongoing studies to assess how climate change will affect the number of rainy days and temperature extremes during the growing season in Mesoamerica.

Fig. 11d shows the climate metric pair that was most descriptive of yield for the Los Santos simulations. Seasonal emulators using the minimum of growing season minimum temperatures and the mean growing season rainfall predict seasonal yields under baseline [CO_2] with an RMSE of 12.8%, and future yields with $r^2 = 0.93$. Paired with growing season mean rainfall, the lowest recorded growing season temperature is actually even more indicative of late season water stress than are December rainfall totals, December solar radiation, or December temperatures as it reflects evaporative demand as the rainy season fades into seasonal drought.

7. Conclusions

The results presented above demonstrate the interacting and competing multi-disciplinary uncertainties that must be addressed in performing a climate impacts analysis on agriculture. The findings underscore the importance of identifying farm-level information to reduce the uncertainties in climate impact assessments on agricultural production, but also show the extent to which a single calibrated model configuration may shed light on many other related farming systems. Even in regions with strong field trial sites, the application of point models to a broader region for aggregation or for other interested stakeholders must consider the prime sources of farm-level uncertainty, either through the end-to-end simulation of multiple farm configurations or through a combination of sensitivity studies at a sentinel location and regional surveys of farm practices and environmental conditions. These approaches are currently being explored as part of AgMIP.

Projections of Panamanian yield under climate change conditions indicate modest increases in production over the coming century. While accelerated crop development is the root cause of yield losses in much of the world, accelerated maize development in Panama helps the grain-filling period complete before the worst water stresses occur, resulting in a net increase in yield.

In general, farm-level calibration uncertainty has a greater influence on baseline performance than on climate impacts analysis, and water-stressed configurations show more positive yield changes under future conditions as accelerated crop maturity and higher [CO_2] reduces the incidence and impact of water shortages. As is apparent in the yield decreases that correspond to the wettest years, however, the opposite is also true and suggests that farming systems with reduced current water stress will experience the detrimental aspects of climate change more prominently. Both baseline and future conditions are quite sensitive to cultivar traits and the selection of soil profile, while large baseline sensitivities to fertilizer amounts are greatly reduced in the future scenarios. Baseline and future simulations for the primera coa season are quite similar to the segunda coa season, and experiments with different fallow period lengths do not substantially alter yields.

GCM projections lead to a wide range of plausible yield impacts with uncertainties increasing in the future. Much of this uncertainty stems from projected trends in Panamanian rainfall, as drier GCMs project yield losses in all future periods. The true climate change signal will be difficult to observe in a region where high interannual rainfall variability obscures long-term trends. Additionally, substantial maize yield gaps in Panama have the potential to be reduced as continuing development allows for a modernization in seed, amendments, and agrotechnology; however these challenges would exist regardless of the additional burdens of climate change.

Bivariate yield impacts response emulators based on CERES-Maize simulations assist in analysis and a first-guess projection of new climate scenarios (particularly when tailored to growing season, rather than annual, metrics), but cannot replace the more complex maize model in Panama. Emulators of future yield must also represent [CO_2] effects, as emulators trained under constant [CO_2] are not useful out-of-sample. One useful product for AgMIP would be to determine the types of simulations that may be adequately performed via a calibrated statistical emulator and to classify the climate change variables (both average and extreme metrics) that crop yields are most sensitive to. For maize yield at our pilot location in Panama, application of quadratic bivariate regressions underestimated the yield impacts of extreme seasons and revealed errors due to the omission of additional crucial metrics including the number of rainy days and the standard deviation of temperatures. In similar regions (where no two variables are capable of predicting yield changes with high skill) AgMIP must continue to rely on dynamic biophysical crop models to investigate climate impacts.

It is hoped that this study will encourage similar analyses (possibly through AgMIP) for other crops and regions to determine what patterns exist in climate impacts uncertainty, and to develop ways of communicating uncertainty to end-users and stakeholders. In order to further address the many uncertainties in climate impacts assessment, an additional study in a region with low yield gaps is currently underway that will evaluate uncertainty in the context of farm-level options and future climate aspects, as in this study, but also on the source of baseline climate information and the types of climate variables allowed to change in future scenarios.

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