

## The Impact of Parameterized Convection on the Simulation of Crop Processes

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### ABSTRACT

Global climate and weather models are a key tool for the prediction of future crop productivity, but they all rely on parameterizations of atmospheric convection, which often produce significant biases in rainfall characteristics over the tropics. The authors evaluate the impact of these biases by driving the General Large Area Model for annual crops (GLAM) with regional-scale atmospheric simulations of one cropping season over West Africa at different resolutions, with and without a parameterization of convection, and compare these with a GLAM run driven by observations. The parameterization of convection produces too light and frequent rainfall throughout the domain, as compared with the short, localized, high-intensity events in the observations and in the convection-permitting runs. Persistent light rain increases surface evaporation, and much heavier rainfall is required to trigger planting. Planting is therefore delayed in the runs with parameterized convection and occurs at a seasonally cooler time, altering the environmental conditions experienced by the crops. Even at high resolutions, runs driven by parameterized convection underpredict the small-scale variability in yields produced by realistic rainfall patterns. Correcting the distribution of rainfall frequencies and intensities before use in crop models will improve the process-based representation of the crop life cycle, increasing confidence in the predictions of crop yield. The rainfall biases described here are a common feature of parameterizations of convection, and therefore the crop-model errors described are likely to occur when using any global weather or climate model, thus remaining hidden when using climate-model inter-comparisons to evaluate uncertainty.

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### 1. Introduction

Agricultural systems are inherently vulnerable to climate variability. This is particularly true in Africa



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where a large fraction of crop production is rainfed (Cooper et al. 2008), making climate a key driver of food security (Gregory et al. 2005). Climate change is predicted to further increase the vulnerability and uncertainty of crop production in Africa, with most studies showing a negative impact, although the magnitude of this impact varies significantly among studies (Challinor et al. 2007; Schlenker and Lobell 2010; Thornton et al. 2011; Knox et al. 2012).

To predict climate-change impacts on crops it is essential to correctly capture the complex and dynamic relationship between crops and climate. Yields can be affected by changes in temperature, water vapor, radiation, and rainfall (Schlenker and Roberts 2009; Lobell et al. 2013; Wheeler et al. 1996), as well as the interactions between these parameters. Different day-to-day variability in temperatures and precipitation can also have a large impact on yields even when the mean conditions are the same (Mearns et al. 1996; Riha et al. 1996).

One method of examining crop yield and climate change questions is to apply statistical relationships between crops and climate (Schlenker and Lobell 2010; Lobell et al. 2008). However, these assume that the relationships remain static in a new climate system. Another method is to use output from a climate model to drive a process-based crop simulation model (Rosenzweig et al. 2014; Thornton et al. 2009; Challinor and Wheeler 2008). These process-based models explicitly simulate crop growth and development and their response to environmental factors. If the key processes are adequately represented, a process-based model has the advantage that it can be applied in a range of locations and climates, which is crucial for exploring the impact of a future climate on crop yield. The behavior of the crop model, however, will also depend on the nature of the climate inputs. For example, the spatial and temporal mismatch between the averaged output from the large grid squares of a climate model and the “point based” spatial scale of an average plant can affect simulated yields by changing surface evaporation rates or the duration of dry spells (Hansen and Jones 2000; Baron et al. 2005; Shin et al. 2010). Errors or biases in the climate-model output itself will also influence the crop-model simulation (Berg et al. 2010), but it is less clear exactly how this uncertainty propagates across models.

To understand and adequately quantify uncertainty in simulated crop yields it is important to better understand the sources of uncertainty in climate-model precipitation and to see how this uncertainty propagates through to crop yield. This is particularly important in West Africa where rainfall is often the limiting factor on crop yields (Bhatnagar-Mathur et al. 2009; Baron et al. 2005) and mostly comes from convective systems with high spatial

and temporal variability. Precipitating cloud systems in all global weather and climate models are subgrid, and so depend on parameterizations of convection, which are a major source of uncertainty in climate models (Christensen et al. 2007). Parameterizations of convection have been shown to produce biases in the representation of tropical rainfall that are qualitatively similar across the majority of models (Moncrieff 2013). In particular, while rainfall totals can be accurate, models have a tendency to rain too often and too lightly when compared to satellite observations, underestimating heavy rainfall events (Randall et al. 2003; Stephens et al. 2010; Sun et al. 2006; Dai and Trenberth 2004; Dai 2006). While there are many possible causes for this bias in the distribution of precipitation, such as the boundary layer or microphysical schemes, comparisons with convection-permitting models suggest that the parameterization of convection is the main source of this error (Pearson et al. 2014; Holloway et al. 2012).

Given the importance of rainfall for crops, both directly and through its indirect impacts on other drivers of productivity, the uncertainty in crop models introduced by parameterizations of convection could be significant both for predictions of climate change impacts and for our understanding of their causes. Limitations to computing power mean that parameterizations of convection will be necessary for the foreseeable future, so developing a process-based understanding of their impact is a research priority. This will allow us to better quantify the uncertainty in crop models caused by the parameterization of convection, and increase our understanding of what specific aspects of the parameterization are causing the most problems.

In this study we quantify the effect of the parameterization of convection on the representation of processes in a crop simulation model. We use three types of atmospheric inputs to drive a crop model: observational data, output from typical weather model simulations using parameterized convection, and output from model simulations where convection is allowed to evolve explicitly, conducted for the first time at very high resolution. The use of these convection-permitting simulations allows us to isolate the role of the parameterization of convection from changes in model resolution or total rainfall amounts.

We describe the models and data used in section 2. In section 3 we present the total seasonal rainfall and crop yield results from all the simulations, to provide context for the subsequent process-based analysis. In section 4 we describe the key biases in the representation of rainfall by parameterizations of convection, and their impact on processes within the crop model. Last, section 5 summarizes the results, describing the implications of

using parameterizations of convection for climate impact studies and which aspects of the parameterizations have the largest contribution to crop-model uncertainty.

## 2. Methods

### a. Weather inputs

#### 1) CASCADE MODEL DATA

As part of the Cascade project a suite of simulations using the UK Met Office Unified Model (UM) were run at resolutions ranging from 4 to 40 km over the entire West African region (from  $-5^{\circ}$  to  $35^{\circ}$ N and from  $-25^{\circ}$  to  $25^{\circ}$ E at 12- and 40-km resolution; from  $0^{\circ}$  to  $28^{\circ}$ N and from  $-20^{\circ}$  to  $20^{\circ}$ E at 4-km resolution) (Pearson et al. 2010). For this study the length of these simulations was extended to cover the period 1 June–24 October 2006, which covers the main monsoon period in semiarid West Africa. The model was initialized with European Centre for Medium-Range Weather Forecasts (ECMWF) analyses. The 40- and 12-km nests were forced at the boundaries by ECMWF analyses and the 4-km nest by output from the 12-km simulations. While the forcing at the boundaries provides some constraints on the large-scale state, the model was allowed to freely evolve within the domain for the duration of the simulation. Two of the simulations were “convection permitting” (horizontal grid spacings of 4 and 12 km) and two were run with “parameterized” convection (horizontal grid spacings of 12 and 40 km). The configurations were set up to be as similar as possible except for the representation of convection, although some details differ. The two 12-km runs in particular are exactly the same except for the use of the parameterization, so that the effects of resolution and the parameterization can be differentiated. The two simulations with parameterized convection both use the Gregory and Rowntree (1990) scheme, but the 40-km run used a relative humidity CAPE closure and the 12-km run used a vertical velocity closure [more details on the impact of the different parameterizations on the simulations can be found in Birch et al. (2014)]. These two simulations were also configured differently in their treatment of cloud–radiation interactions, so that the 12-km simulation would have a configuration similar to the convection-permitting simulations, thus allowing a better comparison between the two 12-km runs, while the 40-km configuration was equivalent to the Met Office operational forecast model.

#### 2) OBSERVATIONS

Observations were used to provide a comparison with the different UM simulations. Rainfall was taken from

the satellite-derived Tropical Rainfall Measuring Mission product TRMM-3B42 at  $0.25^{\circ} \times 0.25^{\circ}$  resolution (Huffman et al. 2007), which combines measurements from multiple satellites, calibrated with the use of surface rain gauges. Shortwave radiative fluxes were derived from the Land Surface Analysis Satellite Application Facility at  $\sim 3$ -km resolution (Geiger et al. 2008). Land surface temperature data from the ECMWF operational analysis were also used (50-km resolution), which combine model simulations with all the surface and radiosonde observations available. As part of the special observation period of the African Monsoon Multidisciplinary Analyses campaign the observational network was greatly enhanced during the 2006 monsoon season (Parker et al. 2008) and some of these observations were submitted to the Global Telecommunications System (GTS) for ingestion into model analyses. All datasets were interpolated onto a  $0.5^{\circ} \times 0.5^{\circ}$  grid ( $\sim 55$  km).

### b. Crop model

The data described in section 2a were used to drive the General Large Area Model for annual crops (GLAM; Challinor et al. 2004). This is a process-based model specifically designed to simulate crops over large areas (i.e., for grid cells comparable to those used in regional and general circulation models). GLAM has been used to simulate yields in both current and future climates in a number of tropical regions including West Africa (Vermeulen et al. 2013; Nicklin 2013; Teo 2006). We used GLAM to simulate groundnut, an important cash crop in the region (Ingram et al. 2002), during the 2006 West African monsoon season. The parameter set used was suitable for Spanish-type groundnut, which is grown across West Africa [for details, see Vermeulen et al. (2013)]. The model was run for the regions in semiarid West Africa where groundnut is grown and for which subnational crop yield data were available, including Senegal, southern Mali, Burkina Faso, northern Ghana, and southwestern Niger (see Fig. 1).

The input data required by GLAM consist of daily weather data, three soil hydrological parameters, and a planting window. The weather variables required are rainfall, downwelling shortwave radiation at the surface, and maximum/minimum surface temperatures. The soil hydrological parameters required are the lower limit, drained upper limit, and saturation limit. These parameters can vary across grid cells but are assumed to be constant with depth. They were calculated from the textural information given in the U.N. Food and Agriculture Organization (FAO) digital soil map of the world. The planting window used in this study was from the start of June until the start of August for all model

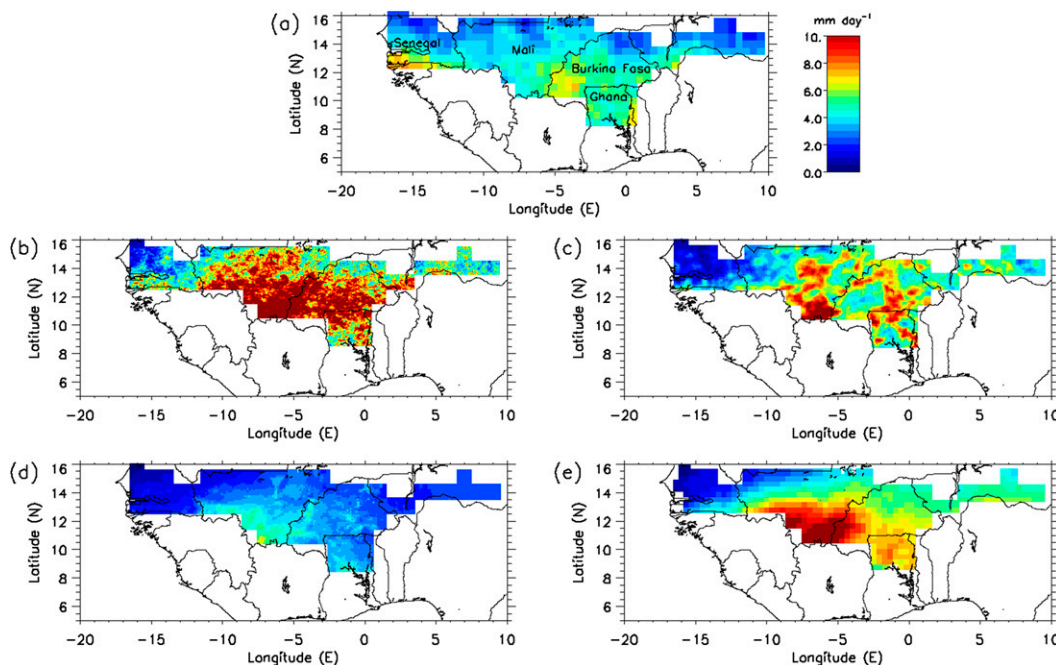


FIG. 1. Mean seasonal rainfall (1 Jun–24 Oct) in (a) ObsWeather, (b) 4Exp, (c) 12Exp, (d) 12Param, and (e) 40Param. Note that in terms of this variable, the use of explicit convection in the model does not automatically improve the results.

grid cells. GLAM uses an “intelligent planting routine” that plants the crop on the first day during the planting window when the soil moisture reaches a given fraction of the water holding capacity. If this criterion is not met, the crop is planted on the final day of the planting window. In this study, the optional process of replanting was also enabled, which allows the crops to be replanted if they fail to become established due to early season water stress (Vermeulen et al. 2013). Replanting was only allowed within the planting window.

GLAM focuses on the response of crops to weather, and uses a single calibration parameter to account for reductions in yield due to nonclimatic factors such as nonoptimal management, pests, and diseases. For this study we set the calibration parameter to 1 for all grid cells, indicating no reduction in yield due to nonclimatic factors. This allows us to study the propagation of uncertainty from climate to crop models, as it ensures that the relationships between crop yields and weather inputs in the simulation are not masked or distorted by the calibration process. A run driven by observed weather is used to describe the crop–weather relationships with realistic weather inputs, and is used to validate the processes in the runs forced by model data.

Crop yield observations are also used for comparison with the crop-model output, from a combination of data from the FAO CountrySTAT database (FAOstat 2012;

<http://faostat3.fao.org/home/E>), the Ghana Meteorological Agency, and the Thematic Data Base Management System (TDBase 2001; “La banque des données tabulaires du Systeme Integre pour l’Alerte Precoce”). Data span the period 1983–2009, although data availability varied by region (Fig. 2a shows the combined average for all datasets).

Five different runs were performed with different weather inputs and resolutions. Four runs were driven by the UM simulations described in section 2a(1). Two of these were convection-permitting (i.e., “explicit” convection) at 4- and 12-km resolution (4Exp and 12Exp) and two used parameterized convection at 12- and 40-km resolution (12Param and 40Param). The final run was driven by the weather observations described in section 2a(2) at  $0.5^\circ$  ( $\sim 55$  km) resolution (ObsWeather). Table 1 provides a summary of the five crop-model runs.

### 3. Rainfall totals and yields

In this section we provide a comparison of the total seasonal rainfall and crop yields in the different runs to provide the context for the more detailed analysis of processes in section 4. The atmospheric model simulations are allowed to freely evolve within the high-resolution domains; despite the constraints imposed by the boundary conditions, there are large differences in

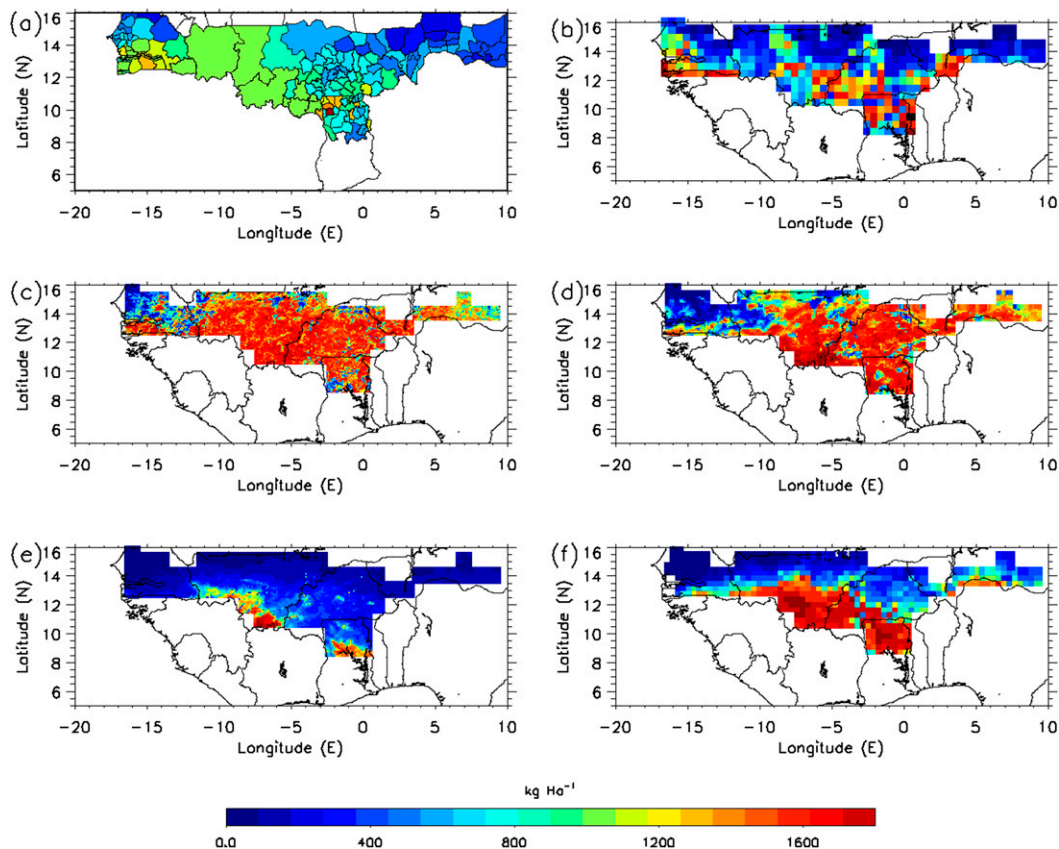


FIG. 2. Groundnut yields from (a) county-level observations averaged between 1983 and 2009, (b) ObsWeather, (c) 4Exp, (d) 12Exp, (e) 12Param, and (f) 40Param. Note that in terms of this variable, the use of explicit convection in the model does not automatically improve the results.

rainfall totals between the runs (Fig. 1). All model runs, except for 12Param, have considerably higher rainfall totals compared to satellite observations. There is a high degree of uncertainty in satellite rainfall estimates, with different satellite products showing a variation of  $\pm 50\%$  over the Cascade domain (Birch et al. 2014). The rainfall in the model simulations, however, is often more than 50% higher than the observations, and is therefore likely to be unrealistic. 12Param, on the other hand, underestimates rainfall in the Sahel, and the differences with 40Param are related to the different parameterization of convection used, as opposed to differences in resolution [further discussion on these differences can be found in Birch et al. (2014)]. The large differences in rainfall amounts between 40Param and 12Param provide an interesting point of comparison; if the two parameterized runs have a consistently different behavior from the convection-permitting runs or observations, this is likely to be caused by the characteristics of the parameterized convection itself rather than any differences in rainfall totals.

In terms of spatial structure, the TRMM observations show a decreasing south–north gradient in

rainfall, with the exception of the most southern area (northern Ghana) where rainfall amounts are lower. Despite the differences in rainfall amounts, both parameterized runs also exhibit a large-scale meridional gradient, and 40Param in particular also captures the maximum in rainfall at  $-5^{\circ}\text{E}$ . The convection-permitting runs, on the other hand, have high rainfall amounts up to the northernmost area of the domain; with the exception of the dip in rainfall over northern Ghana, the large-scale pattern is not as distinct.

TABLE 1. List of GLAM crop-model runs, categorized according to the atmospheric data used as input.

Run name	Atmospheric data	Resolution (km)	Representation of convection
ObsWeather	Satellite obs	55	—
40Param	Model	40	Parameterized
12Param	Model	12	Parameterized
12Exp	Model	12	Explicit
4Exp	Model	4	Explicit

As described in section 2, crop yield observations are not directly comparable to the uncalibrated yields output by GLAM. Some information may be gained, however, by comparing the general characteristics of the simulated yields with the available observations. To capture the mean pattern in yields, the average groundnut yields reported for the full available period of 1983 to 2009 are shown (Fig. 2a). Note that for the larger yield-reporting regions there could be large variations within the region that are not captured. Overall, yields are lower in the observations compared to the ObsWeather results, although the maxima are similar in magnitude (Figs. 2a,b). This is expected given that GLAM has not been calibrated (i.e., the impact of nonclimatic yield-reducing factors has not been taken into account). There is reasonable agreement in terms of the distribution of crop yields, with high yields across  $\sim 11^{\circ}\text{N}$  and in south Senegal and lower yields in northern Ghana and the north and east of the domain. The observations also show high small-scale variability in yields, as can be seen for example throughout Burkina Faso, where crop yields can vary by 100% over distances of 100–200 km. Variability at similar scales can also be found throughout the domain in ObsWeather, despite the relatively coarse resolution of the simulation.

Rainfall is a key driver of yield variability in the study region (Bhatnagar-Mathur et al. 2009; Baron et al. 2005), so many of the differences in the total seasonal rainfall (Fig. 1) are also reflected in the yields. 40Param and the two Exp runs have slightly higher yield maxima than ObsWeather (up to 20%), and high-yield regions cover much larger areas, leading to higher yields overall. Crop yields in 12Param, where rainfall was underestimated compared to observations, are underestimated by up to 75% when compared with ObsWeather throughout large parts of the domain (Fig. 2e), despite the fact that the magnitude of the total rainfall bias is similar to, if not smaller than, that in the other runs. While the convection-permitting runs have high yields up to the northern end of the domain, the parameterized runs have a more realistic large-scale north–south gradient, consistent with the total seasonal rainfall. On the other hand, in the convection-permitting runs yields vary considerably at scales of  $\sim 100$  km, more consistent with observations than 40Param, where the yields vary smoothly throughout the domain. The greater spatial heterogeneity in rainfall in both observations and the convection-permitting runs is likely to be the cause of this variability in yields. This variability is more apparent in 12Exp compared to 4Exp, probably due to the very high domain-mean rainfall in 4Exp producing reasonably high yields even in locations where rainfall

is lower than the mean. Overall there is therefore no clear trend in the accuracy of results regarding resolution or use of parameterization when only evaluating total rainfall and yields in the domain. In the next section, however, we investigate further any differences in the more detailed representation of rainfall and their impact on processes within the crop model.

#### 4. Rainfall biases and their impact on crop processes

##### a. Rainfall frequencies and intensities

One key difference between the convection-permitting/observed and parameterized simulations is how the rainfall is distributed, both spatially and temporally. In the Sahel  $\sim 90\%$  of the rainfall is delivered by mesoscale convective systems (i.e., large, organized clusters of thunderstorms) (Mathon et al. 2002). This means that rainfall is unevenly distributed, with satellite observations showing more than 50% of locations/days with no rainfall, and more than 50% of the total rainfall occurring in high-intensity events (Fig. 3a). The two convection-permitting runs show the same pattern, although the distribution is shifted toward higher rainfall intensities consistent with the overestimation of the seasonal total rainfall, leading to  $\sim 90\%$  of the rainfall occurring in intense events and no rainfall 60%–70% of the time (Figs. 3b,c). Parameterizations of convection, on the other hand, fail to form the organized thunderstorms that are observed, and produce frequent, light rainfall spread over large areas. In both runs the vast majority of rainfall events are light to moderate, with few instances with no (15%–20%) or heavy ( $<10\%$ ) rainfall (Figs. 3d,e).

The differences in resolution between the datasets will affect the profiles shown in Fig. 3, as averaging the data over larger grid boxes will tend to reduce both the highest rainfall intensities and the number of grid points with no precipitation. This alone, however, cannot explain the differences. The satellite observations are the coarsest dataset and have a tendency to underpredict heavy rainfall events compared to rain gauges (Jobard et al. 2011), but despite this they show many more instances of heavy and no rainfall compared to the models with parameterized convection. The atmospheric model runs also show a clear split depending on the use of the parameterization, despite the presence of two simulations run at the same resolution. The similarity in rainfall intensities between the two parameterized runs, despite the difference in resolution and the large discrepancy in seasonal total rainfall between them, therefore points

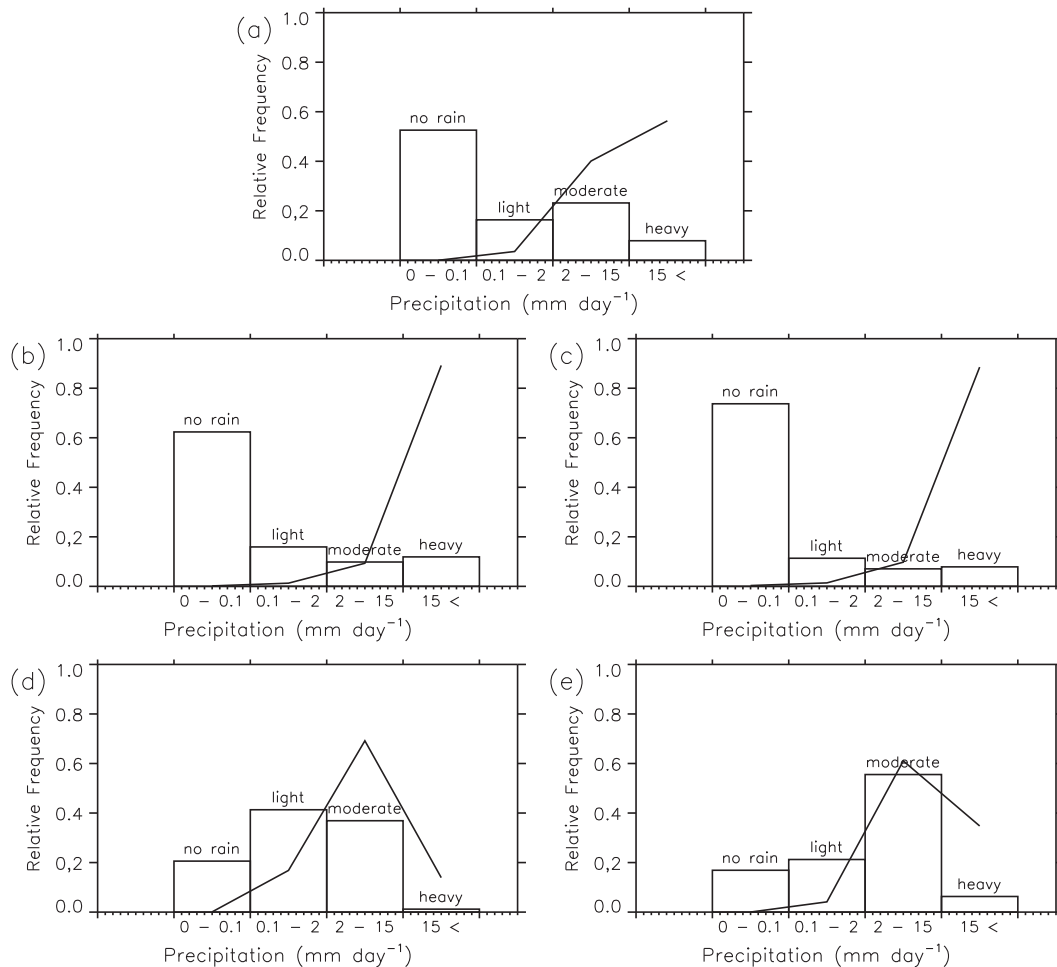


FIG. 3. Fraction of points with no (0–0.1 mm), light (0.1–2 mm), moderate (2–15 mm), and heavy (>15 mm) rainfall (bars), and the contribution to the total seasonal rainfall of each bin (lines) for (a) ObsWeather, (b) 4Exp, (c) 12Exp, (d) 12Param, and (e) 40Param.

toward fundamental shortcomings in the parameterization of convection itself.

*b. Impacts on planting dates via changes in evaporation*

Changes in the rainfall distribution alter the surface hydrology, which is particularly important in determining planting dates. While planting windows can be used to avoid planting at completely unrealistic times within the model, as is done here, it is important that crop models are able to determine planting dates in a realistic fashion, so that they can be used to predict changes in planting dates, as opposed to relying on planting dates as an input. Planting dates also provide a more process-based way of assessing the crop simulations than simply comparing simulated and observed yields.

The large-scale monsoon onset is defined as the relatively abrupt northward shift of rainfall from the coast to

~15°N (Sultan and Janicot 2003). The main rainfall belt reaches 15°N on ~30 July (day 210) in the observations, and this shift is well captured in all runs as it is primarily controlled by large-scale processes, which are constrained by the model lateral boundary conditions (Fig. 4). Farmers, however, tend to plant earlier, during the early-season showers or “local” monsoon onset, in order to maximize the length of the growing season. In all runs there are rainfall events before the large-scale onset in the region 8°–15°N, north of the main rainfall belt, although they are underestimated in 12Param (Fig. 4d) and overestimated in the convection-permitting runs (Figs. 4b,c).

Observed planting dates are typically around May–June in northern Ghana (8°–10°N) and June–July farther north (Portmann et al. 2010; Sacks et al. 2010). The planting dates in ObsWeather and the two convection-permitting runs are consistent with the literature values,

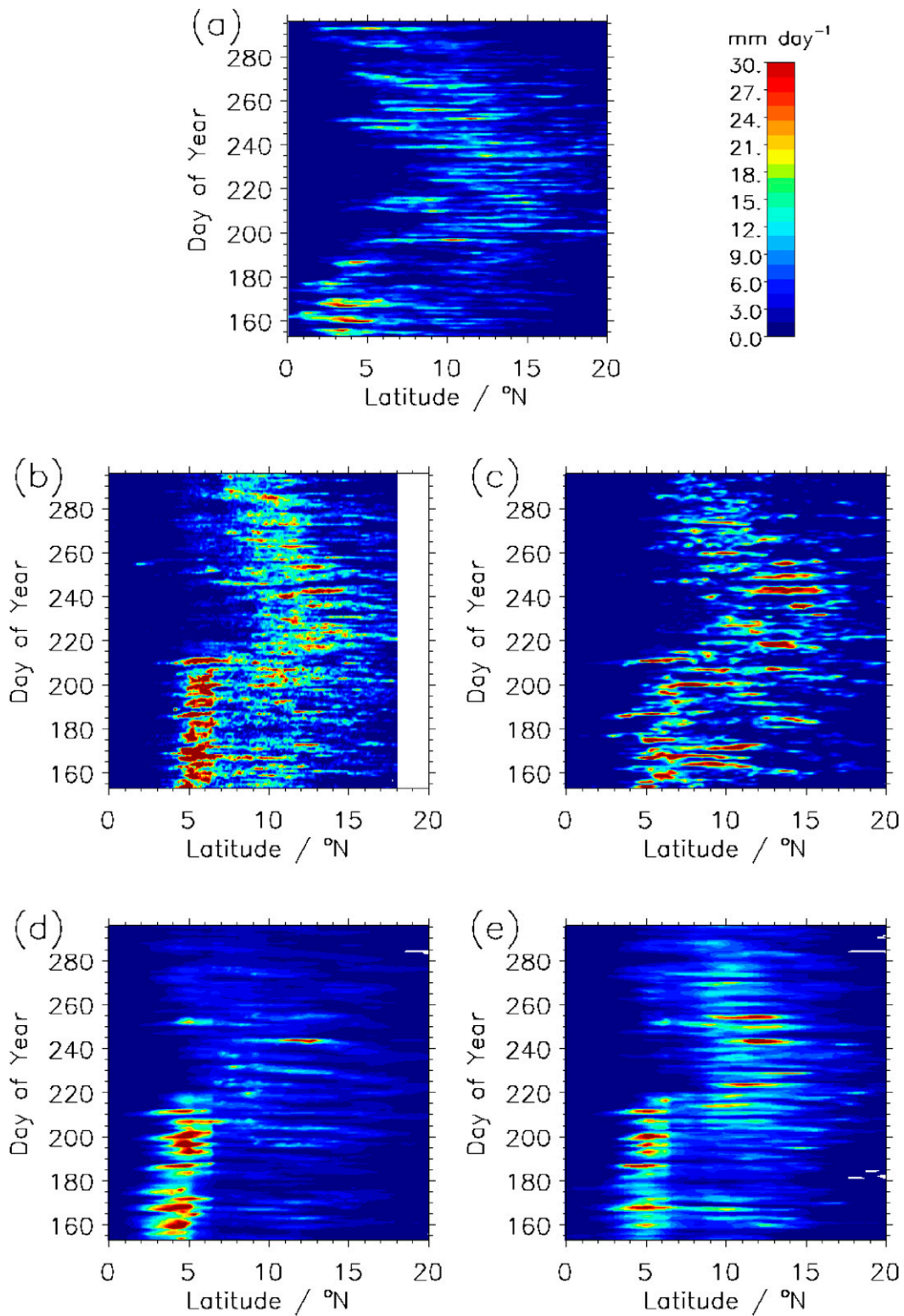


FIG. 4. Seasonal evolution of the zonally averaged rainfall (from  $-10^{\circ}$  to  $5^{\circ}$ E) as a function of latitude in (a) ObsWeather, (b) 4Exp, (c) 12Exp, (d) 12Param, and (e) 40Param.



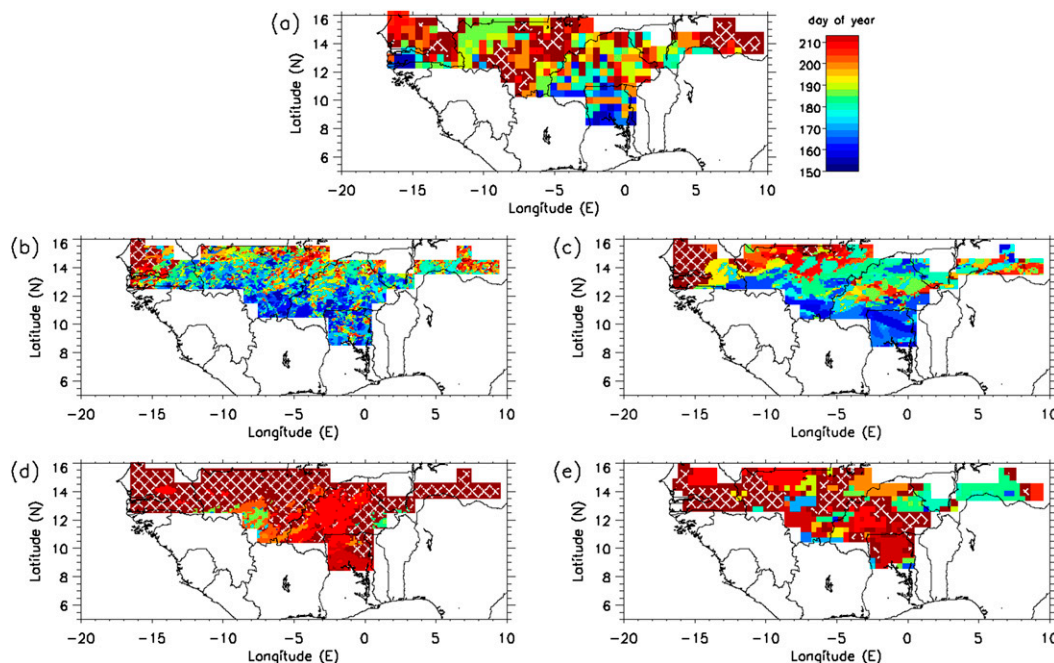


FIG. 5. Planting dates in (a) ObsWeather, (b) 4Exp, (c) 12Exp, (d) 12Param, and (e) 40Param. The white hatching shows regions where the intelligent planting routine was not triggered and therefore planting occurred at the end of the planting window.

with planting occurring at the start of June in northern Ghana, and progressively later (up to the end of July) farther north (Figs. 5a–c). In the runs with parameterized rainfall, on the other hand, planting occurs throughout most of the domain on or after day 210, at the end of July (Figs. 5d,e). Over large areas planting is not triggered before reaching the end of the planting window (white hashing in Fig. 5), and where planting is triggered by the intelligent planting routine, it coincides with the large-scale monsoon onset, when the main rainfall belt moves north. This leads to a delay in planting of nearly two months over northern Ghana.

The two parameterized runs have opposite biases in total rainfall, and in 40Param, delayed planting occurs despite receiving more rainfall than ObsWeather before day 210 (cf. Figs. 4a and 4e, north of 8°N). The intelligent planting routine used by GLAM plants the crop when the soil moisture in the top soil layer reaches a given fraction of the water holding capacity. Differences in the rainfall distribution will alter the availability of water to the crops, by affecting how much rainfall is lost from the soil via evaporation, runoff, and drainage.

Figure 6 shows the fraction of rainfall lost to evaporation before planting. In both parameterized runs more than 90% of rainfall is lost to evaporation. This can be attributed to the presence of persistent light rainfall in the parameterized models, which leads to a daily cycle of light wetting of the upper soil layers, which can

evaporate before the next rainfall event the following day. The early-season rainfall events are therefore insufficient to trigger planting, so planting can only occur when rainfall totals increase substantially with the arrival of the large-scale monsoon onset. ObsWeather, which has lower rainfall than 40Param between days 160–200, has lower evaporation rates, particularly over northern Ghana where the largest discrepancy in planting dates exists. This discrepancy in planting dates is due to the fact that rainfall events are more intense, causing soil moisture to increase enough to trigger planting even when rainfall totals are lower. The overprediction of rainfall totals and maximum rainfall intensities in the two convection-permitting runs leads to increased runoff and drainage (not shown), which is coupled to an underestimation of evaporation. These two effects offset each other, leading to planting dates that are similar to ObsWeather.

It is worth pointing out that evaporation is not a function of the rainfall intensity alone. For example, there are differences in temperature between the runs (discussed further in section 4c), with 40Param having the highest mean temperatures, which will also contribute to increased evaporation. This could explain, for example, the very similar evaporation rates between 12Param and 40Param, despite the higher number of heavy rainfall events in 40Param. However, the overall consistency between the two parameterized runs (which

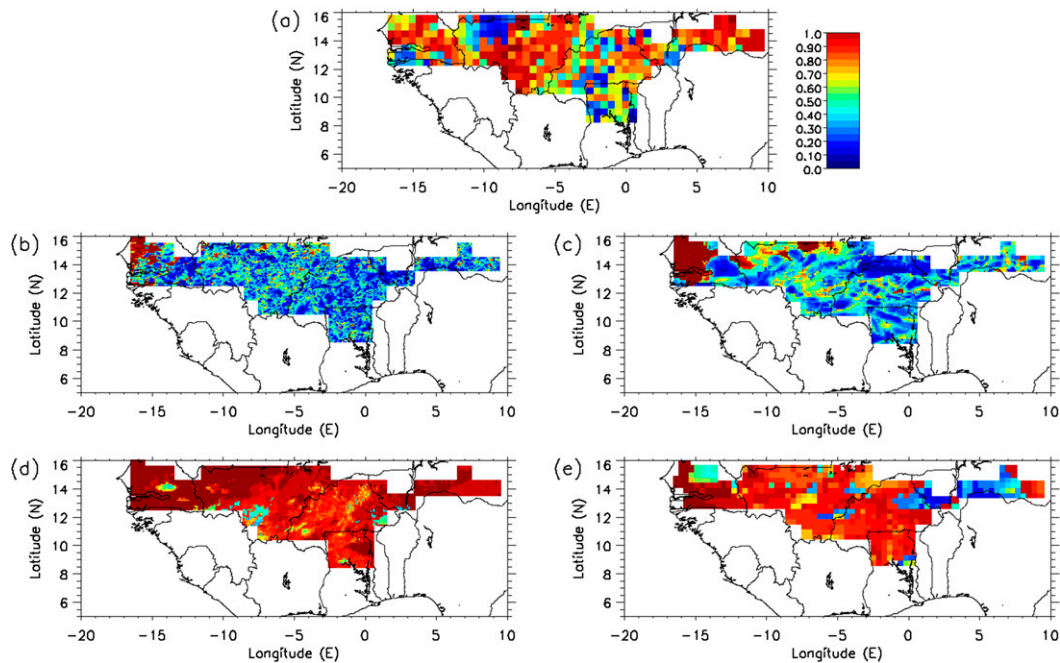


FIG. 6. Fraction of rainfall lost to evaporation from 1 Jun to planting in (a) ObsWeather, (b) 4Exp, (c) 12Exp, (d) 12Param, and (e) 40Param.

have opposite biases in radiation and temperature) and the differences in evaporation between 40Param and ObsWeather, which have similar mean temperatures, suggest that variations in the rainfall distribution are the primary driver of the differences in evaporation.

It could be argued that the convection-permitting and parameterized model configurations are equally incorrect, as they both have evaporation biases of similar magnitude, although of the opposite sign. The cause of the errors, however, is different between the two sets of runs. The issues in the convection-permitting configuration are directly related to an overestimation of rainfall in these runs, which in turn pushes the entire distribution of rainfall in Fig. 3 to the right. If the rainfall totals were closer to observations, for example using a simple multiplicative correction, runoff and drainage would decrease while evaporation would increase. Furthermore, these errors do not affect planting dates, which are therefore similar to ObsWeather, because early-season rainfall is able to trigger planting. The evaporation errors in the parameterized model, on the other hand, are not related to rainfall totals, but to the distribution of rainfall intensities. Evaporation will always be overestimated if rainfall is too frequent and too light, as shown by the presence of similar biases in 12Param and 40Param, despite the large differences in rainfall totals. Therefore, a correct simulation of the planting dates depends critically on correcting the biases in the

rainfall distribution generated by parameterizations of convection.

### c. Impacts of delayed planting on temperatures

Errors in planting dates have indirect effects on the representation of the plant cycle in the crop model. All the atmospheric model runs, as well as the satellite observations used in ObsWeather, show higher surface temperatures early in the season, with a relatively sharp decrease shortly before, and during, the large-scale monsoon onset and a more gradual increase in early September, during the monsoon retreat (Fig. 7a). Because of the seasonal cycle in temperatures (and other variables such as radiation), delayed planting alters the conditions the plant is exposed to when growing, as it will develop at a different time in the seasonal cycle.

Although the shape of the seasonal cycle is very similar between all the runs, there are differences in the actual values even before considering the impact of the planting date. 40Param has the highest temperatures, with differences of 2–5 K with the other model runs before the monsoon onset, decreasing to 1–2 K after the onset. The remaining three runs, however, match closely. The ObsWeather temperatures generally lie between the two sets of models. The mean temperatures, therefore, do not separate clearly between the parameterized and convection-permitting configurations, and resolution or other parameters that make up

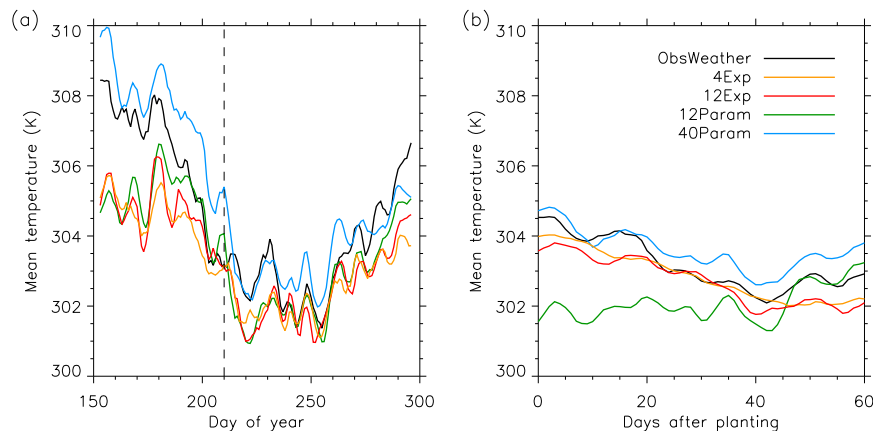


FIG. 7. Domain-mean surface temperature as a function of (a) time and (b) day after planting. The vertical dashed line in (a) indicates the large-scale monsoon onset date.

the model setup appear to be more important. For example, as discussed in section 2a(1), 12Param and 40Param not only use different closures in the parameterization of convection but also handle cloud–radiation interactions differently, which could explain the discrepancy between the two.

The different planting dates affect the temperature experienced by the plant, and so alter the differences between the runs observed in the full seasonal cycle (Fig. 7b). The later planting dates in 12Param and 40Param coincide with the seasonal minimum in temperatures. Therefore, despite the much higher temperatures in 40Param relative to the other model runs, of up to 5 K before the large-scale onset, the temperatures experienced by the crops are only 1 K higher. In 12Param, the even later planting dates lead to lower temperatures at first compared to the other runs, but also an increasing, as opposed to decreasing, temperature trend with time. Temperatures in ObsWeather are slightly higher than the convection-permitting runs, consistent with the full seasonal cycle, due to a closer match in planting dates.

These results show that it is not sufficient to accurately represent the mean seasonal cycle in temperature in order to correctly reproduce the growing conditions for the simulated crops. The representation of rainfall by parameterizations of convection can delay planting even when the seasonal cycle of rainfall is correct, and this in turn affects the conditions experienced by the crops, not only for temperature, but also radiation (not shown). In West Africa temperatures decrease during the first 30–60 days of the plant life cycle, but increase again during the monsoon retreat. Unrealistically late planting dates in crop simulations therefore lead to crops initially growing during the cooler part of the season, which

would cause an underestimation in climate studies of the impacts of rising temperatures. On the other hand, crops would experience higher temperatures close to the end of the crop life cycle. At this time flowering and grain filling occurs, and yields may be more sensitive to temperature differences, thus overestimating the negative effects of rising temperatures. More work is therefore needed to understand what effect dominates in West Africa, and how the processes described in this study affect crop simulations in other tropical regions, in order to better constrain the uncertainty in climate impacts assessments introduced by rainfall errors in atmospheric models.

## 5. Summary and discussion

Parameterizations of convection are a key source of uncertainty in all global climate models, and the biases in rainfall processes that they produce are essentially shared by the majority of parameterizations (Randall et al. 2003; Stephens et al. 2010; Sun et al. 2006; Dai and Trenberth 2004; Dai 2006). For this reason, the impact of these biases cannot be quantified by model inter-comparisons, and their influence on climate change impacts predictions remains largely unexplored. Here we compare satellite observations with model configurations that parameterize convection and with “convection-permitting” configurations, which allow convection to evolve explicitly. The configuration with parameterized convection was run with horizontal resolutions of 12 and 40 km and the convection-permitting configuration was run with resolutions of 4 and 12 km. These different datasets were used to drive a large-area crop model to evaluate the impact of biases in the representation of rainfall on the representation of crops.

The parameterized runs produced an unrealistic distribution of rainfall frequencies and intensities, a well-known issue with parameterizations of convection. The parameterization leads to too frequent light rainfall events (in time and space), with too few heavy rainfall showers and days with no rainfall at all. The bias in total rainfall in the two parameterized runs was of opposite sign, but despite the large differences in total rainfall this persistent “drizzle” was observed in both the runs. The two convection-permitting runs, on the other hand, had rainfall distributions much closer to observations, although peak rainfall intensities and rainfall totals were overestimated.

Despite large differences in rainfall totals between the two runs with parameterized convection (under- and overpredicting rainfall respectively), there were some consistent differences compared to the runs driven by observations and the convection-permitting simulations. Small-scale spatial variability in rainfall, and therefore crop yields, is underpredicted in the parameterized runs, even when the model was run at higher resolutions (12 km, compared to 55 km in the run driven by observations). Spatial variability in rainfall and crop yields is an important factor when assessing the vulnerability of farmers, as regional averages do not quantify the proportion of people in a region that will be affected by crop failures.

The planting dates simulated by the crop model were also markedly different between the runs. In the parameterized runs, planting did not occur before the end of the planting window over large areas of the domain (at which point the crop is automatically planted). Where the planting routine was successfully triggered, it only happened with the arrival of the large-scale monsoon, when rainfall rates substantially increase. In the runs driven by observations and the convection-permitting simulations, planting was triggered earlier, during early-season rainfall events, with planting dates getting progressively later farther north. This is more consistent with the behavior of farmers in the region, and differences in planting dates with the parameterized models were of up to 2 months in the south of the domain. This, in turn, alters the conditions experienced by the crops, as planting in the parameterized model coincides with a seasonal minimum in temperature, which affects the development of the crops. This reduces the mean temperature experienced by the plant, compared to the earlier, more realistic planting dates, but increases temperatures at the end of the plant life cycle, when crops are likely to be more sensitive to temperature changes.

The delayed planting in the parameterized models can be attributed to errors in the rainfall distribution. Persistent light rainfall increases evaporation regardless of

the total rainfall rate, as only the top soil layers are wetted each day, which causes nearly all of the rainfall to be lost to evaporation (>90%) during the start of the season. Much higher rainfall rates are therefore needed for the rainfall to increase soil moisture enough to trigger planting, and so planting can only occur when total rainfall rates increase with the arrival of the main rainfall belt. This issue is independent of the rainfall totals in the model, so a simple correction of the seasonal total rainfall will not address these problems.

Crop models can be tuned to produce a more realistic behavior, for example by constraining planting dates and yields with observations. However, if the biases in the inputs are not addressed, the processes within the crop model will still be unrealistic; the characteristics of parameterized rainfall will always produce excessive evaporation, with not enough water penetrating deep enough into the soil to be taken up by the crops. Another way of looking at it is that, if the processes in the model are incorrect, the tuning has to produce compensating errors to match observations. Observational studies are increasingly highlighting the importance of nonlinear interactions between climatic inputs in order to determine the impact of various environmental stresses on crop yields (e.g., [Schlenker and Roberts 2009](#); [Lobell et al. 2013](#)). It is therefore essential that crop models are correctly simulating these underlying processes. It is not enough for a carefully tuned model to be able to reproduce observations in order to ensure reliable performance in the future, as there is no guarantee that the tunings used will hold when climatic conditions change.

Although the results in this study use a single atmospheric model, similar biases in the rainfall distribution have been identified in other models that parameterize convection ([Sun et al. 2006](#); [Dai 2006](#)), and so this can be considered to be a general shortcoming of any global weather or climate model. The representation of processes within the crop model is improved in the convection-permitting model configurations, as it produces a more realistic rainfall distribution. Although a much higher resolution is required to fully resolve convection, the use of two model runs with the same resolution (12 km) but different representation of convection is evidence that the shortcomings described in this study can be attributed directly to errors in the parameterization of convection. Climate model intercomparisons will therefore suffer from the same issues we describe, and so the model spread will underestimate the true uncertainty.

The atmospheric model used in this study was not calibrated, leading to large biases in total rainfall both with and without the parameterization of convection, which will also contribute to the misrepresentation of processes in the crop model. More typical climate

simulations, however, are much better at representing rainfall totals than its variability (Dai 2006; Sun et al. 2006; Stephens et al. 2010). Improving the rainfall frequency and intensity distributions should therefore be a priority in the development of parameterizations of convection. In the meantime, bias correction of rainfall should tackle this shortcoming directly whenever using climate-model data to drive crop models, for example as done in Ines and Hansen (2006). This will allow a more realistic representation of processes within the crop model. More generally, we propose that a better representation of processes should be prioritized over better quantification of current yields when evaluating and calibrating models, in order to increase our confidence that the model will behave in a realistic way in different climatological conditions.

More work is needed to understand how biases in weather and climate models affect uncertainties in climate impacts predictions. With the current drive to understand the detailed processes that affect observed crop yields, a similar process-based approach is necessary when trying to understand the impact of model biases. Future work should extend these results to consider model runs driven by bias-corrected data, in order to better quantify the uncertainty in past crop-model projections using climate-model data, which did not take into account the biases introduced by the parameterization of convection. This would also help quantify the improvement in model processes achieved by correcting the rainfall frequency and intensity distribution. Further work is also needed to understand the cumulative impacts of the biases presented in this study over the many years for which climate simulations are typically run. Parameterizations of convection have been shown to affect the regional-scale water cycle in West Africa (Birch et al. 2014), and these biases may accumulate over long time periods in unpredictable ways.

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