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What are the dominant features of rainfall leading to realistic large-scale crop yield simulations in West Africa?

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[1] A large-scale crop model is forced by a range of climate datasets over West Africa to test the sensitivity of simulated yields to errors in input rainfall. The model skill, defined as the correlation between observed and simulated yield anomalies over 1968–1990 at the country scale, is used for assessment. We show that there are two essential rainfall features for the model to skillfully simulate interannual yield variability at the country scale: cumulative annual variability and frequency. At such a scale, providing additional information on intraseasonal variability, such as the chronology of rain events, does not improve the model skill. We suggest that such information is relevant at smaller spatial scales but is not spatially consistent enough to impact large-scale yield variability.

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1. Introduction

[2] Agriculture is considered as the most weather-dependant of human activities [*Oram*, 1989]. The interannual variability of crop yields often reflects the variability of weather conditions [*Lobell and Field*, 2007]. In the tropics in particular, fluctuations in climate can lead to severe socio-economic impacts in developing countries [*Challinor et al.*, 2003].

[3] Improved climate prediction offers interesting potential benefits to agriculture: numerous studies have tried to link seasonal prediction outputs from global climate models (GCMs) to crop models, thus translating climate forecasts into seasonal crop predictions (for a review, see *Hansen et al.* [2006]). On longer time scales, combining GCMs and crop models also provides a tool to assess the impacts of future climate change on crop production [e.g., *Jones and Thornton*, 2003].

[4] However, such impact studies ultimately rely on the accuracy of climate input data. GCMs errors inevitably propagate through the combined climate/crop modelling system. In particular, GCMs show systematic biases in rainfall: precipitation patterns are often poorly represented, and rainfall temporal characteristics (frequency, intensity) are biased [*Randall et al.*, 2007].

[5] This study aims at assessing the impact of such errors on the performance of yield prediction. We take West Africa as a case study, which well illustrates the dependence of crop production on climate variability (rainfall, in this case). By progressively correcting model rainfall towards observations, we build successive climate datasets, which are used to drive a large-scale crop model. We analyse how the model skill responds to the quality of the rainfall forcing, and determine what features of rainfall are essential to the accuracy of yield prediction. The model skill is defined as the model ability to simulate the observed time series of yield anomalies at large (i.e., national) scale: only the issue of interannual variability is considered here.

2. Model, Data, and Experiment

2.1. ORCHIDEE-mil

[6] ORCHIDEE is the dynamic global vegetation model developed at IPSL (Institut Pierre-Simon Laplace). When coupled to a climate model, it simulates water, carbon and energy exchanges between the land surface and the atmosphere, explicitly computing vegetation growth [*Krinner et al.*, 2005]. It can also be forced by climate data, to assess the impact of climate on ecosystems.

[7] To account for global vegetation, ORCHIDEE in its standard version uses 10 natural Plant Functional Types (PFT), and two agricultural PFTs. While the standard version essentially approximates croplands by grasslands, a new version has recently been developed for tropical C4 crops (ORCHIDEE-mil) [*Berg et al.*, 2010]. It includes some parameterizations and processes taken from the crop model SARRAH which is routinely used by agronomists over West Africa to simulate tropical cereals like millet and sorghum [*Dingkuhn et al.*, 2003; *Sultan et al.*, 2005].

2.2. Climate Datasets

2.2.1. Rainfall Datasets

[8] Since reanalysis products constitute the most accurate description of weather at the resolution of the GCM, using them as input to a crop model somehow provides an upper limit on the accuracy of the combined (climate and crop) modelling system [*Challinor et al.*, 2005]. We thus use precipitation from the NCEP/NCAR reanalysis [*Kistler et al.*, 2001] as an example of good model output; other products (e.g., ERA-40) could also have been used for such a purpose.

[9] As for rain observations, we use two datasets to span the uncertainty: CRU (Climate Research Unit) [*New et al.*, 1999, 2000] and IRD (Institut de Recherche pour le Développement) data [*Sultan and Janicot*, 2000; *Janicot and Sultan*, 2001] These two datasets are rain gauges measurements interpolated on $1° \times 1°$ grids, but CRU data are only monthly whereas IRD data are daily.

2.2.2. Construction of the Climate Forcing Datasets

[10] We design a range of $1° \times 1°$ forcing datasets for West Africa, in which rainfall is progressively corrected, from model rainfall to observations. Successive corrections

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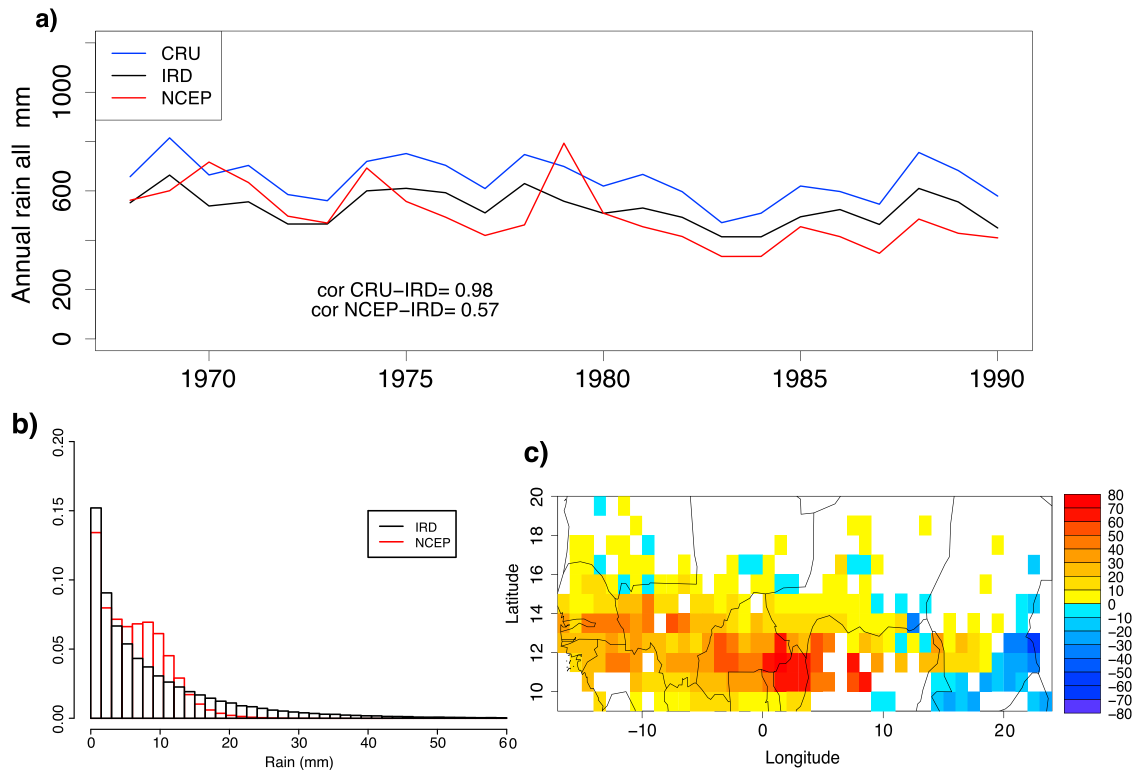

Figure 1. (a) Annual rainfall over 1968–1990, averaged over Mali, Niger Burkina-Faso and Senegal, from IRD, CRU and NCEP datasets. Figures give the correlation between CRU, or NCEP, and IRD. (b) Probabilistic distribution function for daily rainfall amounts from IRD (black) and NCEP (red) datasets, over the whole simulation domain. (c) Difference, in days, between average sowing dates over 1968–1990 in NCEP and IRD simulations (NCEP-IRD); white pixels are IRD missing data.

are applied to NCEP/NCAR rainfall in terms of annual cumulative rainfall, monthly cumulative rainfall, rain frequency. The following climate forcing datasets are built:

[11] 1. NCEP: rainfall is raw NCEP/NCAR rainfall, interpolated on $1^\circ \times 1^\circ$ grid cells [from *Ngo-Duc et al.*, 2005].

[12] 2. NCEP_AR: rainfall is NCEP/NCAR rainfall corrected by annual cumulative rainfall, either from IRD or from CRU. Each year, for each pixel, each rain event in NCEP/NCAR is scaled by the ratio (for that year) of annual rainfall in IRD (or CRU) to annual rainfall in NCEP/NCAR.

[13] 3. NCEP_MR: rainfall is NCEP/NCAR rainfall corrected by monthly cumulative rainfall, either from IRD or from CRU. Each year, each month, for each pixel, each rain event in NCEP/NCAR is corrected by the ratio of monthly rainfall in IRD (or CRU) to monthly rainfall in NCEP/NCAR.

[14] 4. FREQ: IRD daily events are used instead of NCEP/NCAR events; however, each month these events are randomly permuted, in order to lose the real timing of rain events but keep the observed frequency of rainfall. Rainfall is either monthly scaled to IRD monthly amounts or CRU amounts. Note that since total rainfall remains unchanged, the change in rain frequency also means a change in the daily amounts of rainfall.

[15] 5. OBS: IRD daily events are used, either as such, or scaled to CRU monthly amounts. OBS thus has the real frequency and timing of rainfall.

[16] These datasets differ only by their representation of rainfall: in all datasets, variables other than rainfall are NCEP/NCAR variables corrected by CRU data [*Ngo-Duc et al.*, 2005]. Limited by the spatial extension and time period of the IRD data, all these datasets cover a domain of 17°W–20°E, 9°N–20°N, over 1968–1990. The successive corrections applied to NCEP/NCAR rainfall are cumulative: for instance, NCEP_MR has the right monthly cycle and the right annual rainfall.

2.3. Simulations

[17] ORCHIDEE is run off-line over the selected domain, forced with each dataset (over 1968–1990), with a 30-year spin-up on the first year to initialize soil water content. Since we are interested in crop productivity alone, the prescribed vegetation map only includes croplands. Pixels are averaged over each country (below 16°N, the Sahara border) to derive a national simulated yield. Since some data is missing in the IRD rainfall dataset (pixels or years), a common mask *is a posteriori* applied to all simulations to allow comparing the different results. Thus, only the following countries are considered: Mali, Burkina-Faso, Senegal and Niger. National observed millet yields are taken from the FAO database (Food and Agriculture Organization of the United Nations). Since in this study we are only interested in interannual variability, all time series (simulated and observed yields, rainfall) are *a posteriori* linearly detrended.

3. Results

3.1. Main Differences in the Rainfall Datasets

[18] Figure 1a shows that IRD and CRU rainfall datasets are consistent in terms of interannual variability of annual

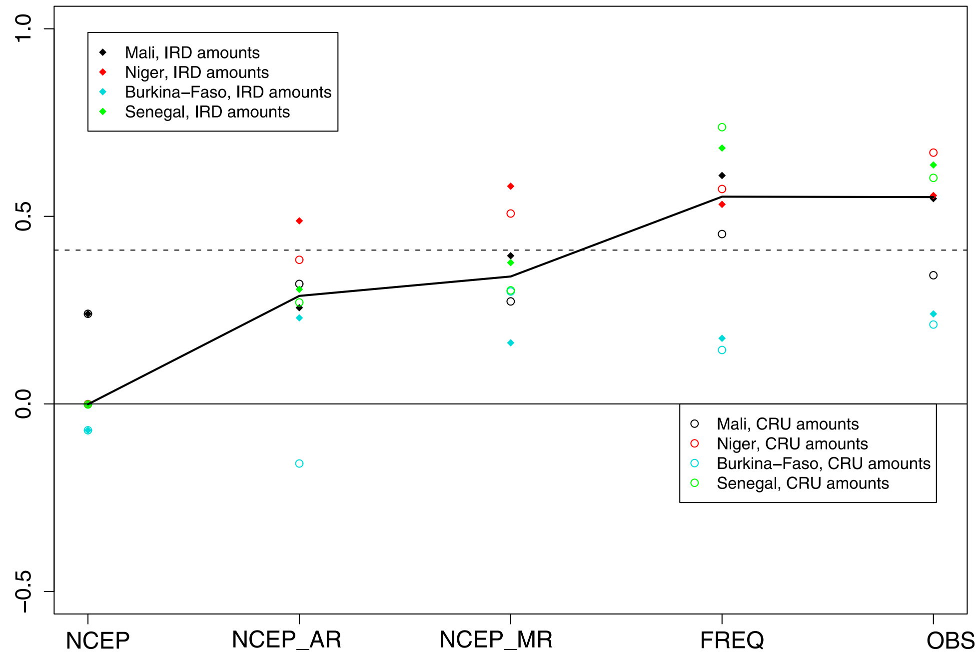

Figure 2. Model score (correlation between observed and simulated yields) across the different simulations, for different countries. The dotted line is the 5% significance level (for a correlation over 23 years). The solid black line is the median score. Colours refer to countries, symbols to the targeted annual amounts (IRD or CRU).

rainfall. However they show large differences in rainfall amounts. NCEP/NCAR, on the other hand, does not accurately capture the observed interannual variability of annual rainfall, as illustrated by the low correlation with observations (either IRD or CRU). In addition, the probabilistic distribution function of daily rainfall in NCEP/NCAR is biased, with too many medium rain events (between 5 and 15mm) and not enough larger events (above 15mm) (Figure 1b). This illustrates the well-known "drizzle rain" bias of climate models. Finally, although NCEP/NCAR correctly represents the atmospheric dynamics of the monsoon (pre-onset, onset [*Sultan and Janicot*, 2003]), first rain events tend to occur too late each year over most of the simulation domain, as shown by the difference in average sowing dates computed by ORCHIDEE-mil between the NCEP and IRD simulations (Figure 1c).

3.2. Model Performance in Predicting Interannual Variability

[19] Figure 2 shows the model score, defined as the correlation over 1968–1990 between observed and simulated annual national yield, for all countries and for each climate forcing. The median score provides an aggregated measure of the model skill over the simulation domain (while not overweighting extreme values). It is nil in the NCEP simulation, but it increases as the rain forcing becomes more realistic, up to 0.55 in the OBS simulation. Most of this increase takes place in two steps: when the right interannual variability of annual rainfall is included (from NCEP to NCEP_AR), and when the right rain frequency is included (from NCEP_MR to FREQ). The median score only becomes significant after this second step. Correcting the monthly cycle or including the real timing of rain events does not substantially increase the median score. Beyond this increasing trend, there is a large dispersion between countries (~0.5), with Burkina-Faso always showing the lowest score, and Niger tending to show the highest one. There are no systematic differences between simulations with CRU or with IRD annual rain amounts.

3.3. Effect of Cumulative Rainfall Variability

[20] Agriculture in Sudano-Sahelian West Africa is mostly water-limited: observed national yields are strongly correlated, on a year-to-year basis, with observed annual rainfall (from CRU or from IRD) (Table 1). Cumulative rainfall is the first-order large-scale "climate signal" [*Challinor et al.*, 2003] in yield data – correlations with other variables are not significant (not shown). Since NCEP/NCAR rainfall is poorly correlated with rainfall observations (section 3.1), FAO yields are not significantly correlated with NCEP/NCAR annual rainfall (Table 1).

[21] Simulated yields in ORCHIDEE are also mostly water-limited: in nearly all cases, simulated yields are significantly correlated with the annual rainfall from the forcing dataset (Figure 3a). As a consequence from these two

Table 1. Correlations Over 1968–1990 Between Observed FAO Yields and Annual Rainfall Either From NCEP Reanalysis or From Observations[a]

	NCEP Rainfall	Observed Rainfall (IRD/CRU)
Mali	0.21	**0.41**/0.32
Niger	0.18	**0.58**/**0.61**
Burkina-Faso	0.15	**0.47**/**0.46**
Senegal	0.26	**0.72**/**0.68**

[a]All time series are linearly detrended. Observations are from IRD or CRU. Correlations significant at the 5% level are in bold.

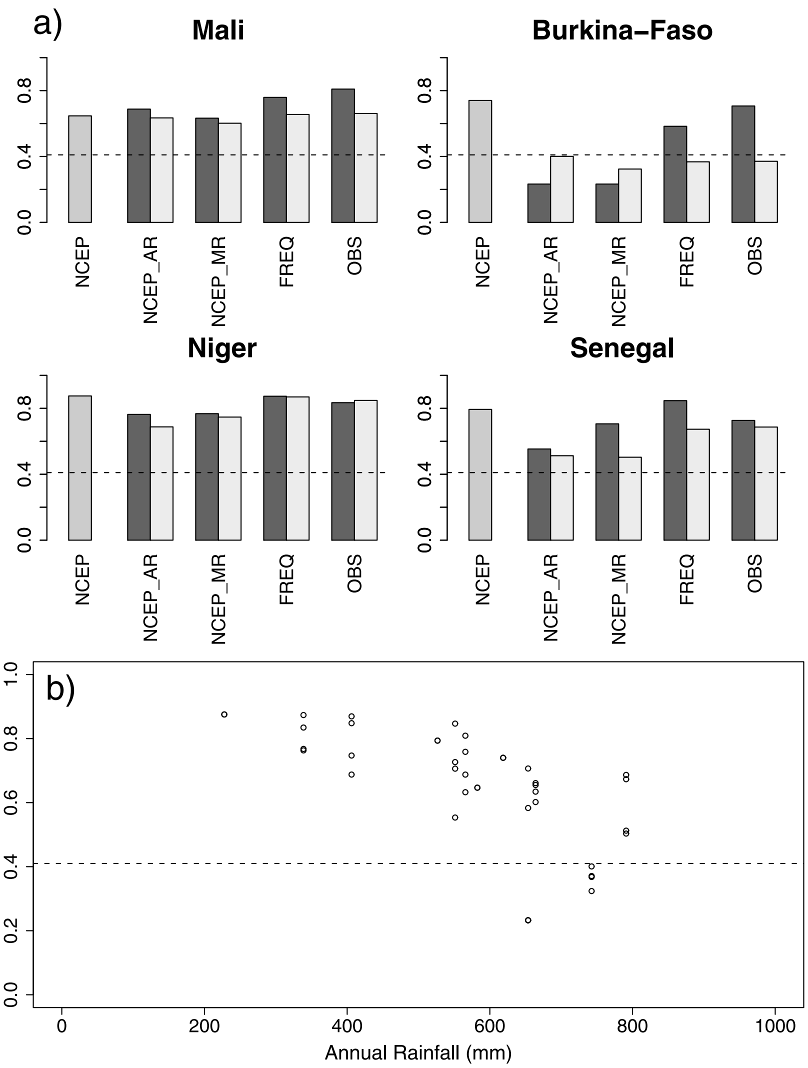

Figure 3. (a) Correlations over 1968–1990 between simulated yields and annual rainfall across the various simulations. Dotted line shows the 5% significance level. Black bars are simulations with IRD annual rainfall, grey bars the ones with CRU annual rainfall. (b) Same correlations, all simulations and all countries, as a function of mean annual rainfall.

relationships (in observations and in the model), yields simulated with NCEP/NCAR can not be expected to correlate well with observations. Conversely, including the proper cumulative rainfall variability, like in NCEP_AR, increases the model score. In other words, one can not simulate yield variability without the right cumulative rainfall variability in input. Since NCEP/NCAR reanalysis can already be considered as a good description of climate at the GCM scale, one may question the ability of any climate model to perform better than NCEP/NCAR in terms of yield simulation.

3.4. Effect of Daily Rainfall Distribution

[22] Between NCEP_MR and FREQ, the model median score increases a second time. This results from a more realistic representation of daily rainfall temporal characteristics (frequency, intensity), since both simulations have the same monthly and annual cumulative rainfall.

[23] The correlation between simulated yields and input annual rainfall increases between the two simulations (Figure 3a). Since observed yields are also strongly correlated to rainfall, this leads, all other things being equal, to a higher correlation between simulated and observed yields.

[24] Simulated yield/rainfall correlations reflect the strength of the water limitation on crop productivity in the model. This is illustrated by the increase in correlations as mean annual rainfall decreases (Figure 3b). For instance, correlations in the NCEP simulation are generally higher because annual rainfall is lower (Figure 1a). Therefore, the higher correlation in FREQ than in NCEP_MR means that rainfall with a proper frequency constrains crop productivity more strongly than "drizzle" rainfall. This can also be seen in the decrease in average simulated yield (not shown): 12% on average for Mali and Senegal. Drizzle rainfall induces a positive bias in simulated plant productivity: small and frequent rain events reduce water stress, increasing the plant's ability to assimilate carbon. This is a well-known bias in crop modelling: using large-scale climate model outputs as forcing tends to artificially increase crop production [e.g., *Baron et al.*, 2005]. Here, we show that it also undermines the model skill, as it weakens the correlation between input rainfall and simulated yield.

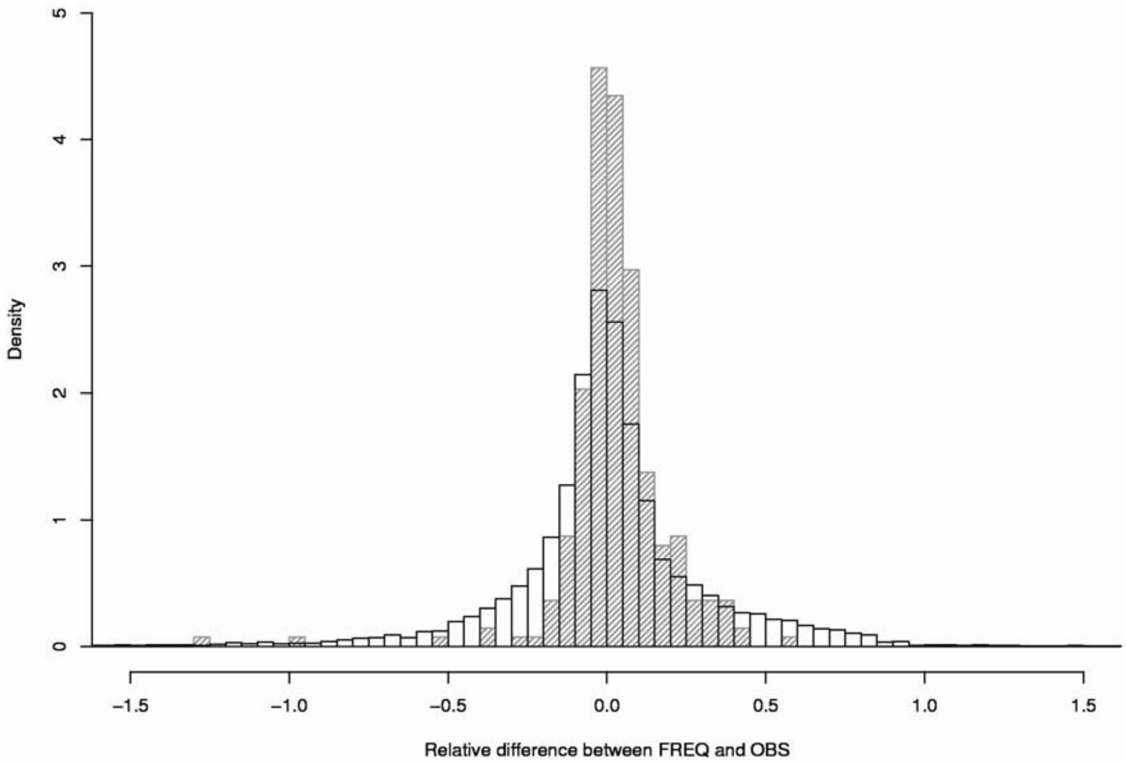

Figure 4. Frequency distribution of the relative differences in yields between FREQ and OBS simulations. Calculations are done at the pixel scale (open bars) and at the country scale (hatched grey bars), all pixels (or countries) and all years considered.

3.5. Effect of Intraseasonal Distribution

[25] The median model score only very slightly increases between NCEP_AR and NCEP_MR. Similarly, there is no increase in model score between the FREQ and OBS simulations. At the scale considered here, information on the chronology of rainfall – whether monthly or daily - does not add to the model skill.

[26] Intraseasonal rainfall chronology has been shown to have significant effects on millet yields in West Africa at plot scale [e.g., *Winkel et al.*, 1997]. Figure 4 shows that the model responds at the pixel scale to the differences in rainfall forcing between the FREQ and OBS simulations. Although we do not have the small-scale yield observations to evaluate the simulations over each pixel, we believe ORCHIDEE-mil, as a process-based model with a daily temporal resolution, is able to capture some of the impacts of rainfall chronology on yields at this scale. However, the aggregation towards national scale substantially reduces the differences between the two simulations (Figure 4): local impacts compensate each other over the whole country. Hence, correlations between simulated and observed yields do not differ between FREQ and OBS. This suggests that intraseasonal distribution variability does not show a spatial consistency large enough to impact simulated yields aggregated on a wider scale. Around each pixel, the area within which intraseasonal rainfall events are significantly correlated is no larger than a few pixels (1.27 on average). Although such results are likely to be resolution-dependant and require further investigation, they suggest that intraseasonal distribution variability is relevant at smaller spatial scales, but is not spatially consistent enough to impact simulated large-scale yield variability. This may further suggest that simple statistical models based on growing season averages can favourably compare at large scale with process-based models [*Lobell and Field*, 2007, 2008]. Here indeed, observed rainfall/yield correlations (tabl.1) are on average similar to the model score when forced by observations (0.53 and 0.55, respectively); however, a fairer comparison would imply an out-of-sample assessment of the statistical relationship. In general, as they do not resolve biophysical processes, statistical models may not perform well when projected under changing climates and environments (for instance, increased atmospheric $CO2$ levels) [*Challinor et al.*, 2003].

4. Conclusion

[27] By forcing ORCHIDEE-mil over West Africa with a range of climate datasets, we assessed the sensitivity of the model skill to different features of rainfall. The two essential rainfall features for the model to skillfully simulate yield variability at the country scale are cumulative annual rainfall variability and rainfall temporal characteristics (frequency/intensity). Although our results are limited to West Africa, we feel confident that they can be extrapolated to similar water-limited crop regions. At such a scale, providing additional information on the intrasesaonal rainfall distribution does not seem to improve the model skill. Whether this last result is resolution- or region-dependant remains to be investigated.

[28] Our results come from a single crop model: their robustness could be further assessed by repeating our anal-

ysis with other models; however, they already give indications on the characteristics of rainfall that climate models should ideally be able to simulate if climate forecasts are to be used to drive crop simulations. The increase in model score in this study, as rainfall is progressively corrected, suggests that improvements in GCM simulations are likely to translate into more accurate yield predictions.

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