Impact of ET0 method on the simulation of historical and future crop yields: a case study of millet growth in Senegal

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ABSTRACT: The reference evapotranspiration (ET_0) is an integrated climatic variable from which many crop models derive simulated crop yields. In most of these models, different equations are parameterized leaving the choice of the equation to the user. However, the impact of the choice of the ET_0 equations on crop yield prediction has been little studied.

The present study proposes a sensitivity analysis of the impact of the choice of the ET_0 equation on simulated millet yields using SARRA-H crop model over 12 Senegalese stations representative of the Sudano-Sahelian climate conditions of West Africa.

Priestley-Taylor, a modified Priestley-Taylor and Hargreaves equations lead to simulated yields up to 19% than those calculated using the Penman-Monteith equation. Despite high biases in wind speed, among the tested methods, the Penman-Monteith method remains the most robust to derive ET_0 and yield over the major part of Senegal, Hargreaves equation being more appropriated under dry climates. The choice of ET_0 formulation introduces uncertainties representing 8% of baseline yield regardless of precipitation changes; for wet conditions these uncertainties approach 30% of the overall climate change impact. The choice of ET_0 equation is increasingly important, with local temperature changes out to 4 °C, while extreme changes above 6 °C depend less on the ET_0 equation.

KEY WORDS evapotranspiration; climate change; West Africa; crop model; modelling; uncertainties; ET_0

1. Introduction

Reference evapotranspiration (ET_0) represents the evaporating power of the atmosphere independently of crop type, crop development and management practices (Allen *et al.,* 1998). In many crop models, this ET_0 (which is sometimes referred to as potential evapotranspiration (PET; Irmak and Haman, 2003)), is the basis to calculate actual evapotranspiration, which takes into account both crop characteristics and soil water availability. Thus, along with precipitation and soil texture, ET_0 is one of the three main drivers of plant water stress and it is likely to have a non-negligible impact on crop development and crop yield simulation. Among crop models, different methods are used to compute ET_0; these methods varying in data requirement from very simple equations requiring average daily temperatures only (e.g. Blaney-Criddle equation; Blaney and Criddle, 1950) to more complex equations requiring daily minimum and maximum temperatures, net radiation, relative humidity and wind speed (e.g. Penman-Monteith FAO 56 equation; Allen *et al.,* 1998). Ideally, crop models should be calibrated before being used to simulate crop yield. The calibration would then occur after the ET_0 method has been set and the adjustment of parameters, such as the crop evapotranspiration coefficient, would compensate for the ET_0 method biases. Yet, all necessary data for crop model calibration are not always available and crop models are used extensively, forced by climate data sets from various origins, without being systematically carefully calibrated. Indeed, many crop models have various ET_0 methods implemented in (Liu *et al.,* 2016), leaving the choice of the ET_0 method to the end user. Roloff *et al.* (1998), Balkovič *et al.* (2013) and Liu *et al.* (2016) showed that the choice of ET_0 equation in EPIC crop model (Williams, 1990) has a significant impact on crop yields simulated over Canada, Europe and continental and Mediterranean climate, respectively. Beyond the accuracy of each of these equations, their robustness when using climate data from other sources and the way errors in climate variables may be propagated to simulated crop yield through the different ET_0 formulation has been little explored up to now. In addition, these different ET_0 equations might have a different behaviour under climate change (Kingston *et al.,* 2009; Barella-Ortiz *et al.,* 2013) and lead to various impacts on projected yields in a future climate.

To calculate crop water consumption, the Food and Agriculture Organization of the United Nations (FAO) recommends the use of the Penman-Monteith FAO 56 ET_0 Equation (PM; Allen *et al.,* 1998). Indeed, among the ET_0 methods available within crop models, the physically

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based PM equation has been shown to be the most reliable over various climates (e.g. Jensen *et al.,* 1990; Allen *et al.,* 1998; Kashyap and Panda, 2001; Yoder *et al.,* 2005; Prudhomme and Williamson, 2013; Liu *et al.,* 2016). However, this equation is highly sensitive to input data quality and it requires climate data that are not always available or reliable or that can be hard to quantify in a climate change context (e.g. wind speed, relative humidity). Kingston *et al.* (2009) raised the question whether it is better to use the most reliable estimates of ET_0 that can be obtained from physically based equations such as PM but with potentially uncertain data inputs, or to use empirical methods of estimating ET_0 that use only the most reliable data inputs such as temperature. Moreover, the PM equation requires the calculation of intermediate variables (e.g. net radiation, aerodynamic resistance) that can be estimated using different methods potentially leading to non-negligible differences in the estimation of ET_0. Then, the pertinence of the choice of the PM equation for impact studies remains highly discussed (e.g. Roloff *et al.,* 1998; Kingston *et al.,* 2009; Sperna Weiland *et al.,* 2012). In regions such as West Africa, where *in situ* climate data are scarce and largely unavailable and where climate models representation of surface variables relevant for crop yield simulations show strong biases, special attention is required when using climate data to derive crop yields. When all the climate variables required for the PM equation are not available, the FAO recommends the use of the Hargreaves (H) equation (Hargreaves and Samani, 1985). This equation is primarily based on temperature and includes extraterrestrial radiation. Yet, many crop models do not use any of the FAO-recommended equations but rather use the Priestley-Taylor approach: LPJ-GUESS (Smith *et al.,* 2001), LPJmL (Bondeau *et al.,* 2007), APSIM (Keating *et al.,* 2003), GLAM (Challinor *et al.,* 2004), PEGASUS (Deryng *et al.,* 2011), STICS (Brisson *et al.,* 2003) and DSSAT (Jones *et al.,* 2003; Hoogenboom *et al.,* 2015). Similar to the PM equation, the Priestley-Taylor (PT) equation is based on net radiation, but it does not include wind speed or relative humidity.

Different equations are then available in crop models and are likely to introduce errors in simulated crop yields if they are not considered during calibration. In a climate change context, efforts are made to project crop yields. Yet, projected changes in crop yields depend on the way climate data are taken into account by the crop model. The use of one or another ET_0 equation can then potentially lead to uncertainties in projected crop yields that need to be quantified to better be considered.

The goal of this paper is to quantify the impact of the choice of the ET_0 method on simulated crop yields using historical and future climate forcing. The impact of the choice of the ET_0 method on simulated pearl millet yields is analysed at 12 contrasted stations located in Senegal, West Africa. This region combines a high vulnerability to climate variability and changes (Schlenker and Lobell, 2010; Roudier *et al.,* 2011; Sultan *et al.,* 2013), scarce *in situ* climate data and strong biases in climate models

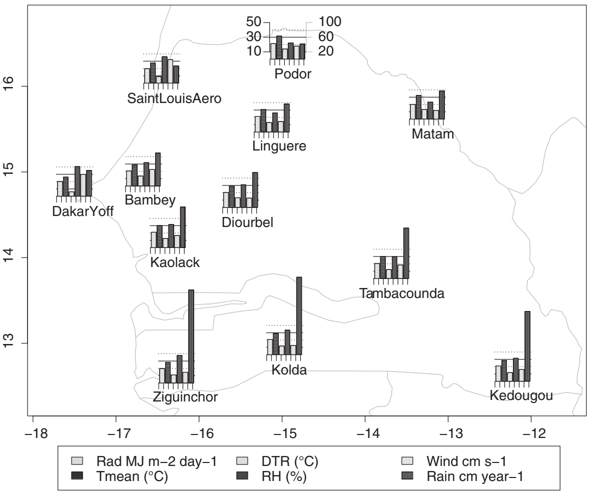

Figure 1. Observed climate variables averaged over 1990–2000 and for the period from 15 April to 20 November (rainy season): incoming solar radiation (horizontal stripes, white) in MJ m^{-2} day^{-1}, mean daily temperature (oblique stripes, white) in °C, daily temperature range (vertical stripes, white) in °C, relative humidity (horizontal stripes, black) in % and wind (oblique stripes, black) in cm s^{-1}. Rainfall (vertical stripes, black) is averaged over the whole year and is expressed in cm $year^{-1}$. The *y*-axis on the right side of the graph applies to relative humidity values only.

in representing surface variables relevant for crop yield simulations (Oettli *et al.,* 2011). The influence of the ET_0 equation on yields simulated using *in situ* weather data is first analysed. Then the impact of the choice of the ET_0 equation on yields simulated using reanalyses and climate model outputs is investigated. Finally, we assess the influence of the ET_0 equation on projected yields in a changing climate.

2. Materials and methods

2.1. Stations and *in situ* weather data

Senegal is located in the Sudano-Sahelian zone of West Africa. This region is characterized by a monsoon climate with a rainy season occurring generally from July to September (Figure 1(b)). The spread of this rainy season and the amount of rainfall vary with latitude from 2 months and 250 mm $year^{-1}$ in northern Senegal to 5 months and 1200 mm $year^{-1}$ in the southern part of the country (Figure 1(a)). The western part of the country is under oceanic influence with high relative humidity, high wind speed and a relatively low daily temperature range (DTR), while the eastern part of the country is more continental with lower wind speed and relative humidity and higher DTR.

Weather data from 12 meteorological stations, distributed across the country (Figure 1(a)) and compiled by AGRHYMET Regional Centre, are used to drive a crop model and to simulate yield. For each of these stations, daily data are available for minimum, average and maximum temperatures, solar radiation, wind speed (at 2 m), relative humidity and rainfall for the 1990–2000 period.

2.2. Climate data from reanalyses and climate models

Meteorological data, except for precipitation, from two other climate data sets were used in this study.

The ECMWF Re-Analysis (ERA) product ERA-Interim, reanalyses of the global atmosphere (ERA-I; Simmons *et al.,* 2007), consists of a set of gridded global analyses at 1.5° resolution and describes the state of the atmosphere, land and ocean wave conditions from 1979 to date. In this study, ERA-I data covering the 1990–2000 period are used at daily time scale.

Climate outputs of a set of nine regional configurations with eight regional climate models (RCM; see Table S2) ran under the ENSEMBLES project multi-model experiment (Van der Linden and Mitchell, 2009) were used as well. These RCM were forced laterally using ERA-I reanalyses and they were run over West Africa for the 1990–2005 period. The outputs of these runs are available over the Analyse Multidisciplinaire de la Mousson Africaine (AMMA) region in West Africa at daily time scale with a resolution of 50 km (Christensen *et al.,* 2009).

In order to obtain a value at each of the 12 studied stations, both data sets were bilinearly interpolated (Oettli *et al.,* 2011). A complete analysis of these weather data can be found in Oettli *et al.* (2011).

2.3. Temperature and precipitation future changes

The set of climate sensitivity test experiments provided by the Coordinated Climate-Crop Modelling Project (C3MP; Ruane *et al.,* 2014) of the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al.* (2013)) is used to derive possible future temperatures and precipitation. This set includes 99 sensitivity tests generated using Latin Hypercube approach (Ruane *et al.,* 2014) and exploring the plausible range of CO_2, temperatures and precipitation changes projected to occur out to the 2070–2099 time period (according to Coupled Model Intercomparison Project Phase 5 (CMIP5) experiment). As the used crop model does not take into account CO_2 fertilization, in this paper, only temperature and precipitation changes are used to derive probabilistic future climate from the *in situ* data described above. Depending on the scenario, daily precipitation are multiplied by a factor going from 0.5 (initial precipitation are decreased by 50%) to 1.5 (initial precipitation are increased by 50%), while daily minimum, average and maximum temperatures are all shifted the same way by a constant going from −1 to +8 °C.

2.4. The SARRA-H crop model

The SARRA-H crop model (Système d'Analyse Régionale de Risques Agroclimatiques version H; Dingkuhn *et al.,* 2003) is a process-based model developed by CIRAD (Centre International de Recherche Agronomique pour le Développement). Designed for cereals, it operates at daily time step and simulates attainable yield at the field scale. Soil texture is implemented in SARRA-H, but mineral balance processes are not explicitly simulated and climate is the main driver for the simulated yield.

The default ET_0 of the model is derived from a PM equation but ET_0 can be calculated offline and prescribed to the model (e.g. Sultan *et al.,* 2013). In the SARRA-H model, calculated or prescribed ET_0 is used in combination with parameters representing crop characteristics and the vegetation cover (depending on crop development) to compute potential evaporation and potential transpiration. The potential evaporation is calculated from ET_0 multiplied by the percentage of soil covered by vegetation; when the soil is totally covered with vegetation, there is no evaporation. Similarly, potential transpiration is calculated from ET_0 and a consumption index that is a function of a coefficient of maximum plant transpiration (depending on plant variety) and a reverse function of the percentage of soil covered by vegetation. The actual transpiration is then calculated from potential transpiration considering the available water within the root zone. Carbon assimilation and biomass growth is reduced by water stress through the plant's satisfactory index, later called Cstr, defined as

$$\text{Cstr} = \frac{\text{Actual Transpiration}}{\text{Potential Transpiration}} \tag{1}$$

Potential yield is calculated from biomass growth, and finally crop yield is computed from potential yield, the plant's satisfactory index Cstr being used to restrict crop development in function of water stress (a more complete description of the processes can be found at http://sarra-h.teledetection.fr/SARRAH_Home_En.html). Simulated yields are thus sensitive to ET_0 through the water stress index (Cstr). The impact of water stress on crop yields depends on the phenological phase at which it occurs. The grain filling phase, at the end of the growing season, is particularly sensitive to water stress.

The SARRA-H crop model was calibrated over Bambey site in Senegal using PM ET_0 equation and Souna 3 pearl millet cultivar. This model is particularly relevant for the analysis of climate impact on cereal growth and yield in dry tropical environments (e.g. Baron *et al.,* 2005; Kouressy *et al.,* 2008; Traoré *et al.,* 2011; Ramarohetra *et al.,* 2013) and it was validated over Senegal (Sultan *et al.,* 2005).

In this study, SARRA-H is used to simulate pearl millet yield of the modern variety Souna 3 (90 days) which is widely grown in Senegal. Pearl millet yield simulations were run at each of the 12 stations with neither fertilization nor irrigation. In this version of SARRA-H, the sowing date is computed automatically according to the following rule, based on observations of farmers' practices: sowing is allowed if there is more than 10 mm of water stored in the upper layer of the soil at the end of the day (i.e. after deduction of evapotranspiration). Note that the model enables the simulation of failed sowings which are an important component of farmers' strategy (Marteau *et al.* 2011). When the simulated biomass growth is negative for at least 11 days during the 20 first days, the sowing is considered to have failed and a new sowing date is calculated following the next heavy rain (see Marteau *et al.*, 2011, for more information).

2.5. ET_0 equations

The ET_0 is the evapotranspiration of a reference surface defined by the FAO as a well-watered 'crop with an assumed crop height of 0.12m, a fixed surface resistance of 70 s m^{-1} and an albedo of 0.23' (Allen *et al.,* 1998). The ET_0 is independent of soil water availability (because it is calculated under a well-watered soil assumption), crop type, crop development and management practices; it is a climatic parameter expressing the evaporating power of the atmosphere.

At daily time step, the FAO (FAO56; Allen *et al.,* 1998) recommends the use of the FAO56 PM combination method. This equation, based on a surface energy balance, requires minimum and maximum air temperatures, solar net radiation, wind speed and vapour pressure. Yet, vapour pressure data are often not available and they are then calculated from relative humidity and temperatures (as it is the case in this study), which can introduce biases. In SARRA-H crop model and in this paper, PM ET_0 is calculated as follows:

$$ET_0\,(PM) = \frac{0.408^{*}\Delta^{*}\left(R_n - G\right) + \gamma\frac{900}{T+273}u_2\ \left(e_s - e_a\right)}{\Delta + \gamma^{*}\left(1 + 0.34^{*}u_2\right)} \tag{2}$$

where Δ is the slope of the vapour pressure curve (kPa °C^{-1}), γ the psychrometric constant (kPa °C^{-1}), R_n the net radiation at the crop surface (MJ m^{-2} day^{-1}), G the soil heat flux (MJ m^{-2}.day^{-1}), not included in FAO56 method, T the average daily air temperature at 2 m height (°C), u_2 the wind speed at 2 m height (m s^{-1}), e_s the saturation vapour pressure (kPa), e_a the actual vapour pressure (kPa) and $e_s - e_a$the saturation vapour pressure deficit (kPa).

In this study, this equation is used as a baseline for comparison with the others equations.

Indeed, it is highly rated across a wide range of climates (Allen *et al.,* 1998; Kumar *et al.,* 2012) and often used as a reference standard, including in semi-arid environments (e.g. Chiew *et al.,* 1995; Gavilán *et al.,* 2006; Zarei *et al.,* 2015; Djaman *et al.,* 2016) and tropical environments (e.g. Kra, 2014). Moreover, PM ET_0 is the one used by default in the used crop model, SARRA-H, that is designed for West Africa semi-arid environment.

When all the climate variables required to calculate the PM equation are not available, the FAO recommends the use of H equation (Hargreaves and Samani, 1982, 1985) to approximate ET_0. This equation was developed to be used in cases of not available radiation data. However, it attempts to capture the seasonality of radiation by incorporating the incoming radiation at the top of the atmosphere (or extraterrestrial radiation), which can be calculated from latitude and the day of the year. This extraterrestrial radiation does not capture the surface incoming radiation day-to-day variability due to changes in cloud cover and atmospheric transmissivity. Such effects are only roughly approximated through their impact on temperature and daily temperature range:

$$ET_0\,(H) = a^{*}R_a^{*}\,(T + 17.8)^{*}\,DTR^{0.5} \tag{3}$$

where a is an adjustment coefficient (°C$^{-0.5}$) either set to its default value 0.0023 or locally calibrated, R_a the extraterrestrial radiation (MJ m^{-2} day^{-1}), T the average daily temperature at 2 m height (°C) and *DTR,* the daily temperature range, which is the difference between the maximum daily temperature and the minimum daily temperature at 2 m height (°C).

Many crop models rather use the PT equation (Priestley and Taylor, 1972), which is based on net radiation and replaces the aerodynamic term of the PM equation by a dimensionless parameter α:

$$ET_0\,(PT) = \frac{\alpha}{\lambda}\ \frac{\Delta^{*}\left(R_n - G\right)}{\Delta + \gamma} \tag{4}$$

where Δ is the slope of the vapour pressure curve (kPa °C^{-1}), γ the psychrometric constant (kPa °C^{-1}), R_n the net radiation at the crop surface (MJ m^{-2} day^{-1}), G the soil heat flux (MJ m^{-2} day^{-1}), λ the latent heat of vaporization (MJ kg^{-1}) and α the adjustment coefficient.

The α coefficient is set to its default value 1.26, adjusted locally or partly calculated, using the Steiner *et al.* (1991) equation(e.g. GLAM crop model; Challinor *et al.*, 2004). Steiner *et al.*'s α equation involves vapour pressure deficit calculation and then requires relative humidity data in addition to the data required by the 'traditional' PT equation. Steiner *et al.*'s α parameter, noted here α', is calculated as follows:

$$\alpha' = 1 + (\alpha - 1)^{*}\,k^{*}\left(e_s - e_a\right) \tag{5}$$

where e_s is the saturation vapour pressure (kPa), e_a the actual vapour pressure (kPa) and $e_s - e_a$ the saturation vapour pressure deficit (kPa), α the PT empirical parameter (default value = 1.26) and $k = 1$ kPa^{-1} an artefact to make the equation dimensionless.

Hereafter, the PT equation using the initial α parameter will be called PT, while the PT equation using the α' parameter will be called PT_S.

2.6. ET_0 equations calibration

H and PT parameters and the α coefficient in PT_S equation were adjusted for each station, (Table S1) so that, over the April to October 1990–2000 period, the average ET_0 is the same as PM's. Note that, since the sowing date varies for each year and each site and the growing season (about 90 days) is shorter than the considered period for the calibration, one can observe differences in mean ET_0 during the growing season from one equation to another (Figure 2).

2.7. Data analysis

In this analysis, ET_0 and yields calculated using *in situ* weather data are considered as baseline. Then, ET_0 and yield calculated using other climate data are

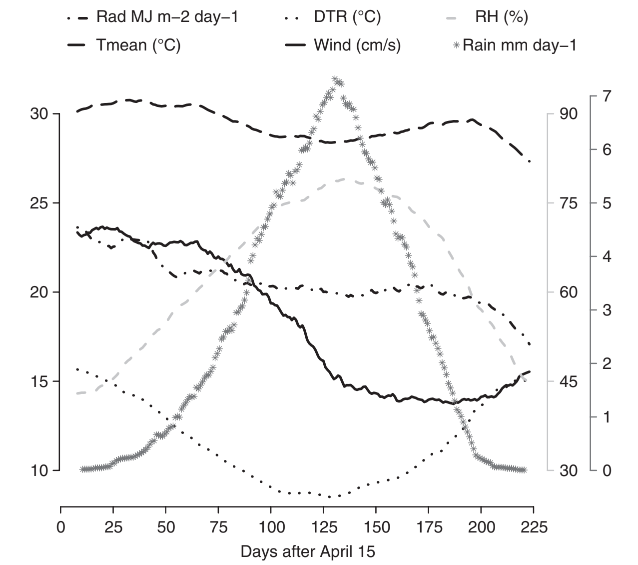

Figure 2. Variations of observed climate data during the rainy season and averaged over 1990–2000 and the 12 stations. Fifteen days moving average for radiation (dotdashed line) in MJ m^{-2} day^{-1}, mean daily temperature (longdash line) in °C, daily temperature range (dotted line) in °C, daily averaged relative humidity (dashed line) in % and daily averaged wind (solid line) in cm s^{-1} and daily mean rainfall in mm (stars). The *y*-axes on the right side of the graph apply respectively to relative humidity and rainfall values.

compared to baseline using relative deviation (in % of the baseline):

$$\text{relative deviation} = \frac{1}{N}^{*} 100^{*} \sum_{i=1}^{N} \frac{\left(x_i - x_{0i}\right)}{x_{0i}} \tag{6}$$

where x_{0i} is the value of ET_0 or yield of the baseline and x_i the value of ET_0 or yield to be tested.

For the first analysis, for which only *in situ* weather data are used, the value taken as baseline is the average of the values calculated using the different equations.

In the following section, we first use *in situ* weather data to calculate ET_0 and yield and we analyse the difference in results as a function of the chosen ET_0 equation. Then, we use alternative climate data (data from ERA-I reanalysis, either directly or after a dynamic downscaling) to calculate ET_0 and yield and study how the ET_0 are changed compared to baseline. Finally, the influence of the chosen ET_0 equation is investigated in a climate change context, and baseline temperature and precipitation values are then altered following C3MP set of sensitivity tests.

3. Results

3.1. Uncertainties of different ET_0 methods by using *in situ* weather data

When averaged over the crop cycle, calculated ET_0 varies depending on the chosen equation (Figure 3(a)). Over Senegal, the ET_0 deviation from mean ET_0 goes from −4.45% for PM to +7.2% for PT (Figure 3(a) and Table 2). Differences in ET_0 result in differences in simulated crop yields, reaching up to 33.13% of the mean yield (Figure 3(b) and Table 2) on average over the country. However, the crop yields deviation from mean is not a linear function of integrated ET_0 deviation from mean.

These differences in ET_0 and yield derived from the selection of ET_0 methods reflect distinct local situations: divergences in ET_0 are the lowest in moist environments (high relative humidity in Dakar and Ziguinchor; Figure 1 and Table 2) and the highest in hot and dry environments (Podor, Matam), while divergences in simulated yields are the lowest where water is not a (or a less) limiting factor for crop development (Ziguinchor and Kolda) and the highest where water is scarce (Podor, Matam, Saint-Louis). Most often, the higher the ET_0, the lower the yield; this being modulated by the precipitation amount. Indeed, for the same amount of available water higher ET_0 leads to higher water stress, leading itself to less simulated yields. However, it is not always the case and the most noticeable example is the one of PT in Podor. There, a relatively high ET_0 (+9.48% from mean) leads to a relatively high yield (+34.55% from mean).

To understand this result, one must look at the intraseasonal variations of the ET_0. In fact, depending on the chosen equation, the variations of ET_0 during the rainy season differ (Figure 4(a)). PM ET_0 intraseasonal variations are mainly driven by both wind speed and relative humidity variations (Figure 2), while PT_S ET_0 variations are rather driven by relative humidity. H ET_0 variations are linked to the daily temperature range and PT ET_0 seems to follow radiation variations. As a result, on average, during the growing season, PT ET_0 remains about the same, around 5.46 mm, while PM, PT_S and H ET_0 vary. PM and PT_S ET_0 reach their minimum value between the end of the reproductive phase and the beginning of the grain-filling phase, while it is attained at the beginning of the reproductive phase for H ET_0. During these most sensitive crop growth phases [reproductive phase (3) and grain-filling phase (4)], PT ET_0 is higher than the others, followed by PT_S ET_0, H ET_0 and PM ET_0. Consequently, the evaporative demand of the atmosphere during sensitive phases is, on average, the highest for PT ET_0 leading to a higher probability of water stress. Since the sowing date and the rainfall pattern (rainfall intensity and timing) can vary substantially depending on the simulated year and location, these average trends of ET_0 variations during the growing season cannot directly be translated into impacts on crop yields, each case should be studied in more detail. In Podor, during the growing season, PT ET_0 decreases, while it remains about the same (PM and PT_S) or tend to increase (H) for the other equations (Figure 4(b)). Then, for PT, the water stress due to atmospheric water demand decreases during the growing season, leading to an increase in biomass growth and resulting in the estimation of high potential yields. Yet, water stress is relatively low during the grain filling phase what results in final yields close to potential yields. As a result, although on average ET_0 PT is high, its influence on crop growth dynamics lead to higher yields than expected from mean ET_0 value: intraseasonal variations of the ET_0 can lead to significant differences in simulated yields.

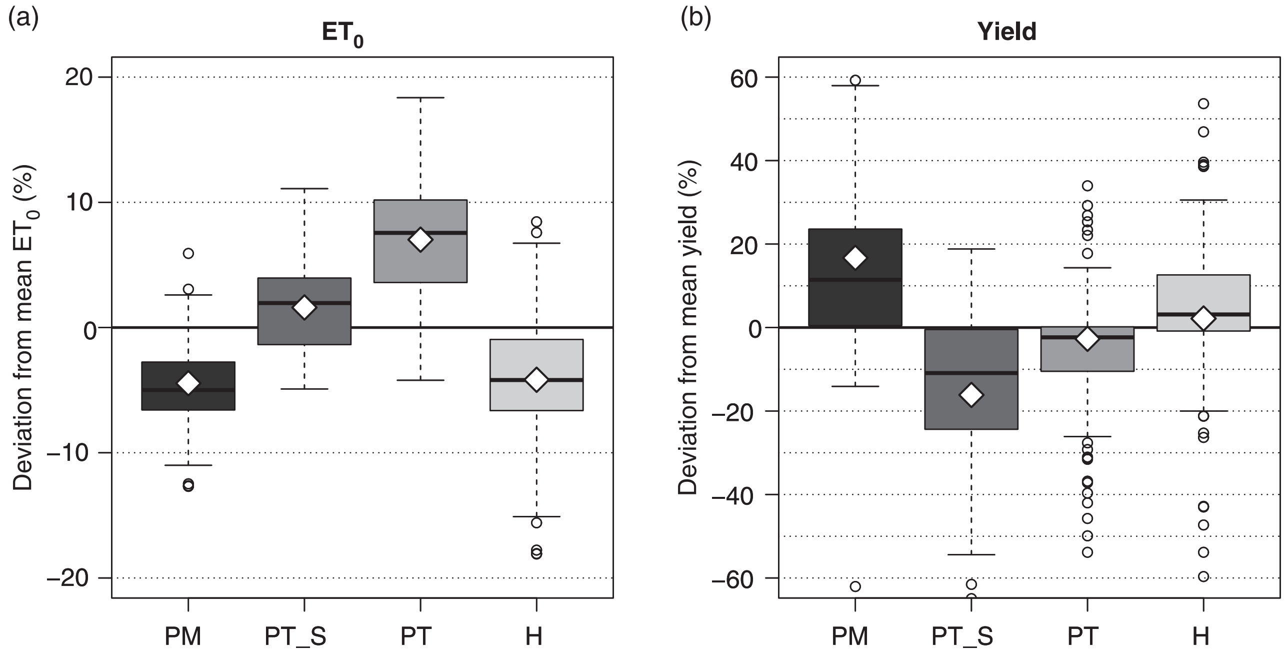

Figure 3. Deviation from mean of ET_0 and yields calculated using *in situ* climate data for each equation: PM, PT_S, PT and H. (a) Deviation of the calculated ET_0 over the crop cycle with respect to the average of these calculated ET_0 (all equation) for each ET_0 equation (*x*-axis) and for each station (dispersion). The white diamonds represent the mean for each ET_0 equation. (b) Same as (a) but for simulated yields.

Table 1. ET_0 and yield deviation from mean for each station.

		Stations												Mean
		Bambey	Dakar	Diourbel	Kaolack	Kedougou	Kolda	Linguere	Matam	Podor	Saint-Louis	Tambacounda	Ziguinchor	
ET_0 anomalies														
	PM	−5.04	−3.43	−5.11	−5.65	−2.01	−0.38	−6.32	−6.75	−7.76	−5.15	−2.62	−3.17	−4.45
	PT_S	−2.19	2.53	4.2	1.87	1.95	6.43	2.21	4.71	−1.24	−2.79	−1.87	3.43	1.6
ET_0 equation	PT	10.26	0.53	7.9	8.88	5.88	3.14	10.53	9.85	9.48	7.88	7.54	2.34	7.02
	H	−3.02	0.37	−6.99	−5.1	−5.82	−9.18	−6.43	−7.81	−0.49	0.07	−3.04	−2.59	−4.17
	Range	15.3	5.96	14.89	14.53	11.7	15.61	16.96	17.66	17.24	13.03	10.16	6.6	11.47
Yields anomalies														
	PM	18.14	16.2	12.09	14.92	4.12	0.65	14.11	48.2	21.7	46.29	6.41	0.11	16.91
	PT_S	−16.88	−3.01	−12.12	−17.34	−5.76	−0.04	−21.55	−35.28	−42.16	−25.22	−15.33	0.05	−16.22
ET_0 equation	PT	−0.16	2.04	−15.36	−12.6	−5.04	−2.75	−4.56	−15.62	34.55	−17.84	3.92	−0.28	−2.81
	H	−1.1	−15.23	15.38	15.01	6.69	2.14	12	2.71	−14.09	−3.23	5	0.12	2.12
	Range	35.02	31.43	30.74	32.35	12.45	4.89	35.66	83.48	76.71	71.51	21.74	0.4	33.13

Weather data = *in situ* observations.

Different climate variables influencing the different ET_0 can lead to distinct year-to-year variability of the ET_0: H ET_0 interannual variability is significantly different from the other ET_0 interannual variability for most stations (Table 2). However, these differences in ET_0 interannual variability do not influence simulated yields interannual variability, which is mainly driven by the variability of precipitation and then remain similar from one equation to the other.

3.2. Uncertainties of different ET_0 methods by using ENSEMBLES data

In this section, the impact of the choice of the ET_0 equation on simulated yields is studied when using reanalysis and downscaled reanalysis from the ENSEMBLES experiment (later called ENSEMBLES climate).

The upper part of Table 2 shows the deviation of ENSEMBLES climate variables when compared to *in situ* weather data. The values of the deviation are very heterogeneous, spatially and from a variable to another. Wind shows the highest deviations with values, ranging from +23.95% to +101.59%. Wind deviation is particularly high in the northeastern part of the country (Diourbel, Linguere, Podor and Matam stations) and may induce important biases in the PM ET_0 calculation. Radiation deviation is less important; it ranges from +2.13% to +17.22%, and it shows the same spatial trends as wind with higher values in the north than in the south of the country. DTR deviation is systematically negative with especially high values in Dakar (−31.69%). Relative humidity deviation from baseline is relatively low going from −7.52% to +6.42%.

Table 2. Correlation coefficient of interannual variations of ET_0 averaged over the growing season and yields for the 1990–2000 period (11 years).

	Interannual correlation coefficient R							
	ET_0				Yield			
	PM	PT_S	PT	H	PM	PT_S	PT	H
Bambey	**1**	**0.87**	**0.79**	**0.64**	**1**	**0.91**	**0.88**	**0.73**
Dakar	**1**	**0.93**	**0.79**	0.09	**1**	**0.99**	**0.93**	**0.88**
Diourbel	**1**	**0.92**	**0.7**	0.43	**1**	**0.91**	**0.81**	**0.89**
Kaolack	**1**	**0.98**	**0.86**	**0.68**	**1**	**0.95**	**0.94**	**0.95**
Kedougou	**1**	**0.95**	**0.89**	0.27	**1**	**0.97**	**0.8**	**0.96**
Kolda	**1**	**0.88**	**0.78**	−0.1	**1**	**0.97**	**0.96**	**1**
Linguere	**1**	**0.91**	**0.78**	**0.64**	**1**	**0.98**	**1**	**0.98**
Matam	**1**	**0.8**	0.29	**0.83**	**1**	**0.99**	**0.98**	**0.99**
Podor	**1**	0.52	0.13	0.48	**1**	**0.92**	**0.99**	**0.99**
Saint Louis	**1**	**0.83**	**0.67**	0.24	**1**	**0.99**	**0.97**	**0.99**
Tambacounda	**1**	0.52	0.02	0.21	**1**	**0.97**	**0.92**	**0.94**
Ziguinchor	**1**	**0.95**	**0.85**	0.51	**1**	**0.99**	**1**	**1**

Values significant at 5% level are highlighted in bold.

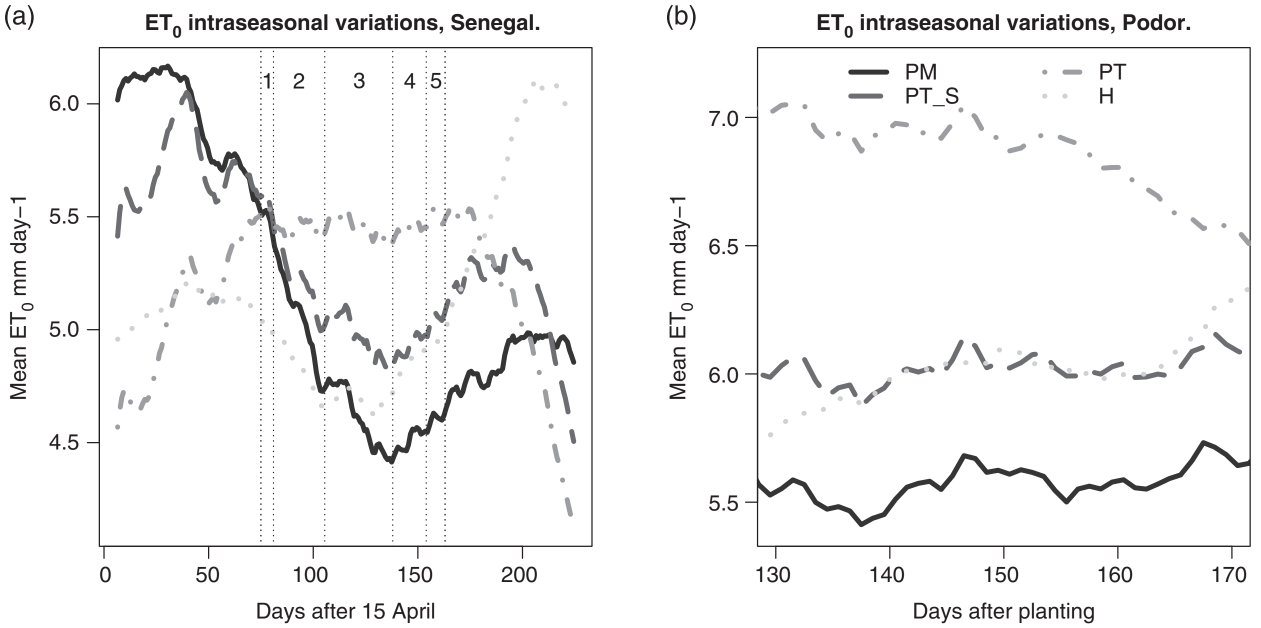

Figure 4. Intraseasonal variations of ET_0 for each equation: PM (solid line), PT_S (longdashed line), PT (dotdashed line) and H (dotted line), 45 days moving average of ET_0 in mm day^{-1} (a) during the rainy season and on average over the 12 stations and for the 1990–2000 period and (b) during the growing season in Podor and on average over the 1990–2000 period. On Figure 4a, the numbers show the average timing of each phase delineated by dotted lines: (1) emergence, (2) juvenile phase, (3) reproductive phase, (4) grain filling and (5) dessication.

When *in situ* weather data is replaced by ENSEMBLES climate, changes in the direction and in the amplitude of the calculated ET_0 and yield vary depending on the considered Equation. H mean ET_0 is reduced by −12.72% on average, while PM, PT_S and PT mean ET_0 are increased by up to 40.79% on average (Figure 5 and Table 3). Indeed, depending on the considered equation, deviation from reference of growing season ET_0 mean values is driven by different climate variables: mean PM ET_0 deviation is mainly driven by wind speed deviation (Figure 6 and Table 3), mean H ET_0 is mainly driven by daily temperature range, while mean PT ET_0 is mainly driven by solar radiation.

Yield deviation from baseline depends also on the ET_0 considered: for H and PT equations yields are increased when compared to baseline by, on average, 43.41% and 27.49%, while for PM and PT_S equations yields are decreased by −15.93% and −7.62%, respectively (Figure 5(b)). These differences in yield when using ENSEMBLES climate rather than *in situ* data vary a lot depending on the considered location and can be very important locally with differences reaching more than 20% (Table 3).

3.3. Future climate sensitivity experiments

The previous results have shown that the choice of the ET_0 equation has a non-negligible impact on simulated yields under present climate. In this section, the impact of the

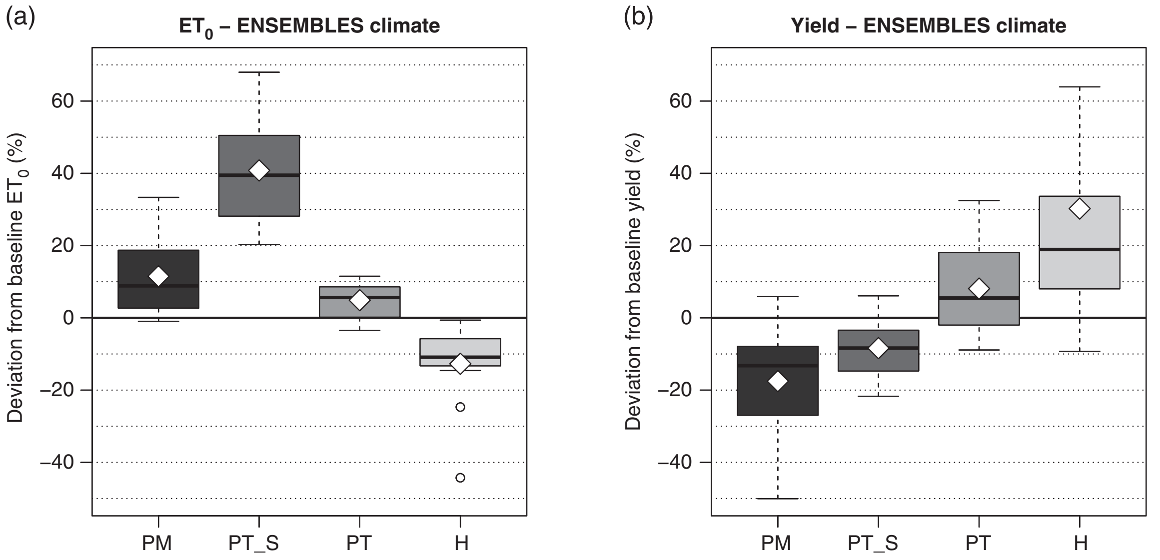

Figure 5. Deviation from baseline ET_0 and yields calculated using ENSEMBLES climate data for each equation: PM, PT_S, PT and H. (a) Deviation of the calculated ET_0 over the crop cycle with respect to calculated ET_0 using *in situ* data for each ET_0 equation (*x*-axis) and for each station (dispersion). The white diamonds represent the mean for each ET_0 equation. (b) Same as (a) but for simulated yields.

Table 3. Climate data, ET_0 and yield deviation from reference for each station.

	Stations												Mean	Range
	Bambey	Dakar	Diourbel	Kaolack	Kedougou	Kolda	Linguere	Matam	Podor	Saint-Louis	Tambacounda	Ziguinchor		
Climate data mean deviation from reference														
SW radiation	10.06	10.91	10.58	6.56	2.31	2.13	10.42	15.54	13.48	17.22	7.77	4.93	9.33	15.09
Daily temperature range	−20.71	−31.69	−11.97	−11.67	−18.44	−17.53	−2.52	−12.87	−7.49	−6.35	−12.77	−23.10	−14.76	29.18
Relative humidity	1.72	−1.91	−0.03	0.85	6.42	2.27	−0.92	−3.16	−0.43	−7.52	0.20	−0.63	−0.26	13.94
Wind	32.34	40.88	78.69	49.08	27.77	46.40	85.30	101.59	93.19	23.85	33.73	30.80	53.63	77.74
ET_0 deviation from reference														
PM	3.99	8.35	12.96	4.93	1.41	−0.95	21.46	33.35	27.57	15.96	9.36	−0.32	11.51	34.30
PT_S	36.58	20.28	32.01	37.68	46.22	41.28	49.89	58.81	67.98	23.37	51.09	24.30	40.79	47.70
PT	5.40	5.97	5.39	−0.17	0.56	−3.46	7.37	11.01	9.76	11.51	5.87	−0.50	4.89	14.98
H	−14.60	−44.25	−10.13	−11.96	−11.66	−11.93	−0.64	−6.08	−3.88	−5.49	−7.34	−24.69	−12.72	43.61
Range	51.18	64.54	42.14	49.64	57.88	53.21	50.53	64.89	71.86	28.86	58.43	48.99	53.51	
Yield deviation from reference														
PM	−7.17	−28.72	−12.57	0.62	−7.99	−11.51	−20.29	−45.50	−38.17	−17.99	−7.17	5.34	−15.93	50.84
PT_S	−9.45	−19.73	−8.13	4.64	−7.08	−9.35	−6.82	−17.48	0.59	−17.30	−6.81	5.54	−7.62	25.27
PT	−0.38	1.28	6.62	15.72	−3.54	−8.09	19.00	10.80	29.52	17.23	−3.23	3.36	7.36	37.61
H	35.55	138.79	15.33	25.62	−2.06	−8.43	10.13	19.07	22.80	58.11	10.47	4.47	27.49	147.22
Range	45.00	167.52	27.90	25.01	5.93	3.42	39.28	64.57	67.70	76.10	17.64	2.19	43.41	

Weather data = ENSEMBLES climate.

choice of the ET_0 on yield prediction under future climate scenarios is studied.

First, temperature changes only are considered. Figure 7(a) shows a linear relationship between the calculated ET_0 and temperature whatever the considered equation. H ET_0 is the least sensitive to an increased temperature with a linear regression coefficient of 2.11, while PM ET_0 is the most sensitive to temperatures with a linear regression coefficient of 2.66. PT and PT_S have a linear regression coefficient of 2.55. Temperature rise induces a quasi-linear decrease of simulated yields (Figure 7(b)). Simulated crop yields decrease by 6.6% for an increase of temperature of 1 °C when H equation is used to a decrease of −7.7% of yield per increase of 1 °C when PT_S equation is used. This decrease in crop yield driven by temperatures is consistent with the literature (e.g. Thornton *et al.*, 2007; Schlenker and Lobell, 2010). The influence of the choice of the ET_0 equation on crop yield change increases until reaching a maximum representing up to 10% of baseline for a change in temperatures of about +4 °C, it stabilizes then decreases once temperature change reaches 6 °C. Indeed, different processes involving temperature lead to yield losses: (1) an increase in evapotranspiration that can amplify water stress, this process is ET_0 equation dependent, while the others are not, (2) high temperatures can have a direct impact on plant tissues (e.g. the lethal temperature for the considered cultivar, 44 °C, can be reached several times during the growing season), (3) an increase in respiration per biomass unit leads to less biomass (then grain yield) production

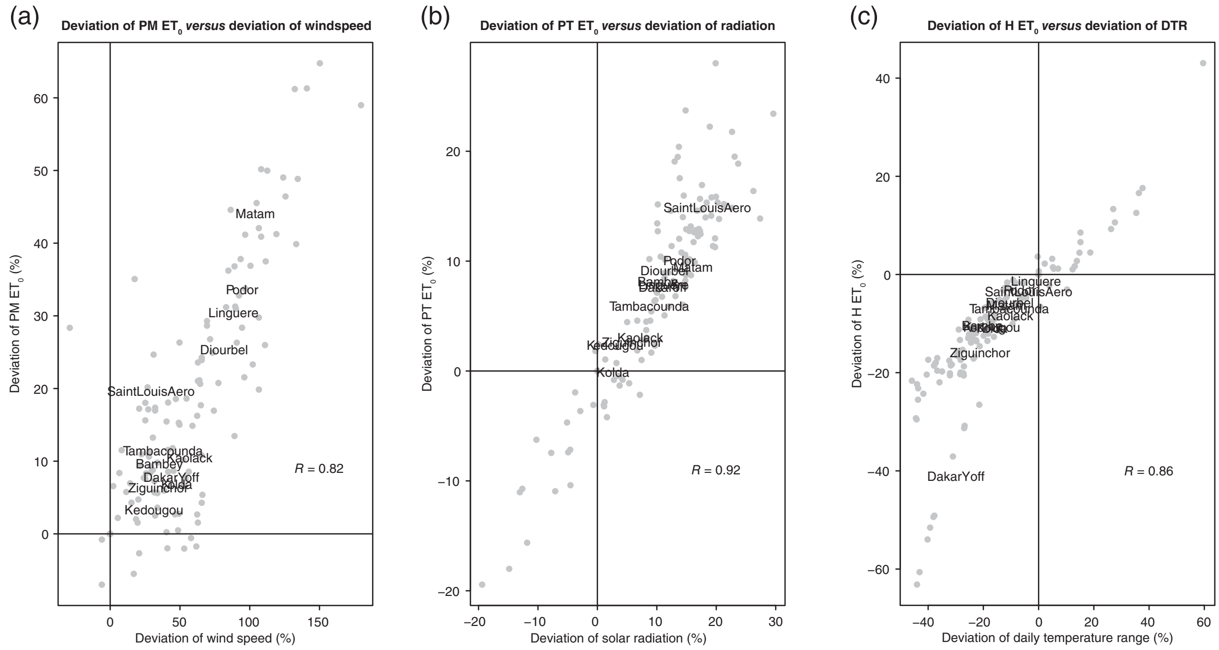

Figure 6. Deviation from baseline of ET_0 as a function of climate variables deviation from *in situ* values for (a) PM ET_0 and wind, (b) PT ET_0 and solar radiation and (c) H ET_0 and daily temperature range. The position of the average deviation for each station is represented by the name of the station. *R* is the coefficient of correlation between the two variables.

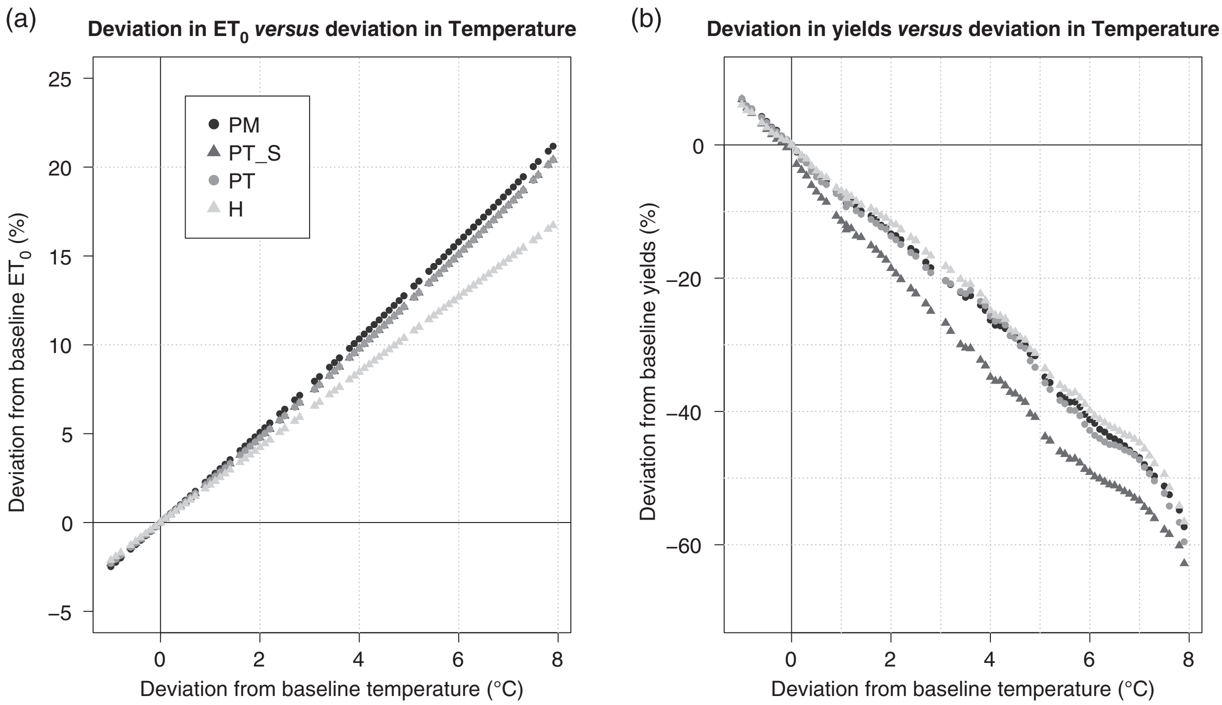

Figure 7. Calculated ET_0 (a) and yields (b) deviations from baseline against temperature (Tmin and Tmax) deviation from baseline for each equation: PM, PT_S, PT and H.

and (4) a reduction of the crop-cycle duration reduces in turn yield production. The higher the temperature, the more temperature driven processes independent from ET_0 equation are at play.

Figure 8(a) shows that an increase in temperature ranging from +4 °C to +5 °C combined with a decrease in precipitation results in a simulated yield average reduction ranging from −68.11% (PT_S) to −60.49% (H). For the same increase in temperatures but for an increase in precipitation (Figure 8(b)), simulated yields average reduction goes from −11.28% (PT) to −20.81% (PT_S). The highly negative impact of low rainfall decreases the relative impact of the choice of ET_0, whereas in the case of an increase in precipitation, the choice of the ET_0 equation has a relatively high impact (the average decrease in yield is almost divided by two between PT_S and PT). The

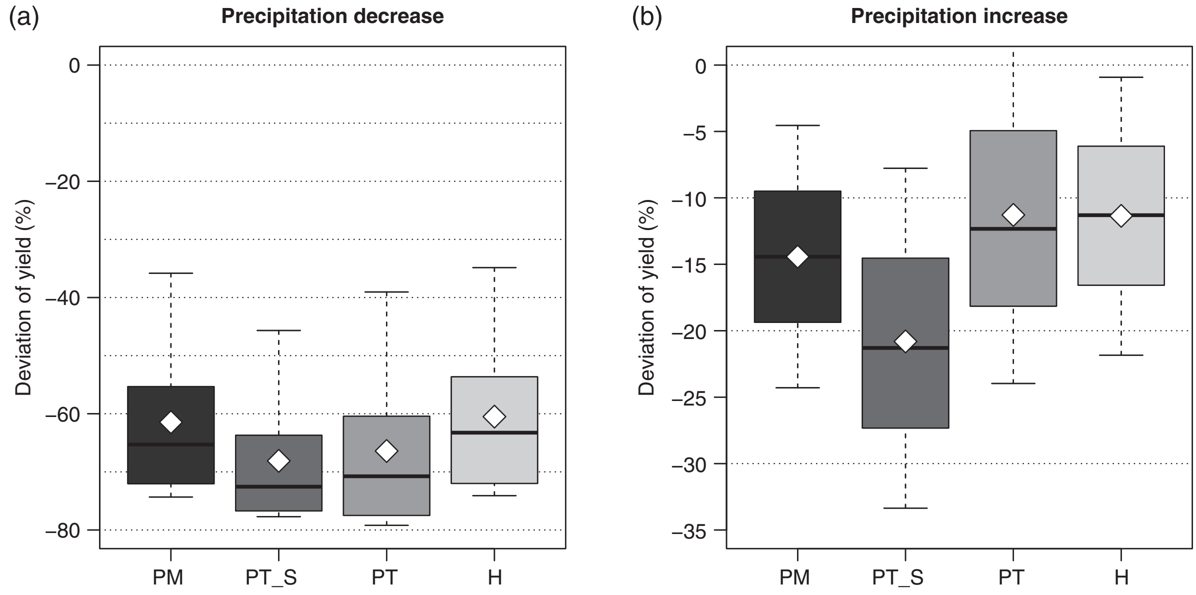

Figure 8. Deviation of simulated yields for an increase of temperatures between +4 °C and +5 °C for each equation: PM, PT_S, PT and H and for (a) a decrease in precipitation and (b) an increase in precipitation. The white diamonds represent the mean values.

negative impact of increased temperatures on simulated yields is hardly compensated by an increase of precipitation; when temperatures shift exceeds +2.3 °C, the impact of temperatures and precipitation changes on crop yield is negative even for an increase in precipitation of more than +50% (not shown). This is consistent with previous studies (e.g. Schlenker and Lobell, 2010; Sultan *et al.,* 2013) and meta-analyses (e.g. Roudier *et al.,* 2011; Knox *et al.,* 2012).

Although on average over Senegal, a decrease in precipitation tends to lower the relative impact of ET_0 equation on simulated yield reduction, the importance of ET_0 equation is location dependent (Figure 9). Indeed, the combined effect of an increase in temperature and a decrease in precipitation is very different for southern humid stations – with Ziguinchor showing a simulated yield decrease of about −25% – and northern dry stations – with Podor, Saint Louis and Matam simulated yields losses exceeding −80%. For most of the stations with initial total precipitation higher than 350 mm (south to Dakar), the ET_0 method induces non-negligible uncertainties in calculated crop yields, PT_S method being the most sensitive to changes, while H method is the least sensitive. For example, in Kolda, simulated yields decrease ranges from −28% (H) to −44% (PT_S).

4. Discussion

This study focuses on the impact of the ET_0 formulation on crop yield. When using *in situ* weather data, ET_0 and yield derived from H equation are the closest to the baseline: ET_0 and yield derived from PM equation. This is consistent with FAO recommendation to use the H equation as a substitute for the PM equation when all the data required by the PM equation are not available (Allen *et al.,* 1998) and it is consistent with Liu *et al.* (2016) who found that H equation was a valid alternative option for all regions except for high-rainfall regions.

When using reanalyses and RCM climate data, depending on climate characteristics of the area, either the PM or H equation is the most robust equation for ET_0 and crop yield calculation. The location and climate characteristics of the stations where these equations perform the best are consistent with the results of previous studies. For example, the H equation is found especially robust over semi-arid stations of the northern part of Senegal, indeed this equation was first calibrated in this area: the first empirical coefficient was set using data from Senegal River basin semi-arid area (Hargreaves and Allen, 2003) and indeed Liu *et al.* (2016) found that H equation tends to overestimate evapotranspiration over humid regions. On the other hand, when driven by reanalyses and RCM climate data, the H equation shows particularly low robustness over Dakar windy low DTR station, highly underestimating ET_0 there. This is partly due to high DTR biases over this station. It comes also from the fact that, for Dakar station, the relationship between the mean bias error (%MBE) of DTR and ET_0 is quite different from the others (Figure 6(c)), which is consistent with Gavilán *et al.* (2006). Indeed, taking the PM ET_0 as a reference, the authors showed that, at coastal areas, the H equation tends to underpredict the PM ET_0 and it is generally less accurate for windy locations where DTR is low (as in Dakar). The PM equation, on the contrary, is found the most robust over more humid climate. Indeed, the FAO PM method for computing ET_0 requires weather data measured in an environment with healthy vegetation not short in water (Allen *et al.,* 1998, Annex 6). Thus, we expect that the PM ET_0 estimation is the most robust in the wettest stations of Senegal.

Among the limits of this study, the H, PT and PT_S ET_0 methods could not be calibrated using measured ET_0

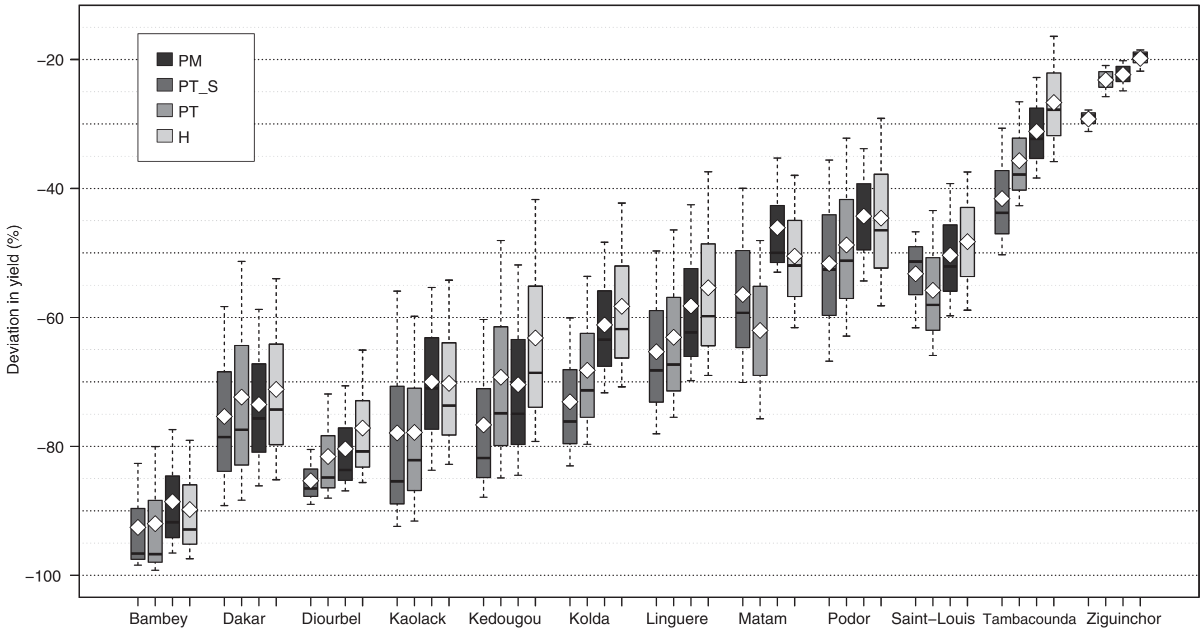

Figure 9. Deviation in yield for each ET_0 equation and each station (from north, on the left, to south, on the right) for a decrease in precipitation and an increase in temperature by about 4 °C (between 3.8 °C and 4.2 °C).

and were thus calibrated with PM ET_0 as a common baseline. In addition, the *in situ* weather data used to calculate baseline ET_0 and yield are not 'reference' weather data as required by the FAO PM equation. Consequently, the baseline ET_0 might be overestimated under dry conditions (Allen *et al.,* 1998). When the behaviour of ET_0 and yield calculated under temperatures and precipitation changes is studied, none of the ET_0 equations is taken as the baseline equation. Yet, equations involving adjusted coefficients are more likely to become inaccurate under a changing climate and the most physically based PM equation might be the most reliable method. Another limit relies on the fact that the increase in CO_2, known to modify stomatal conductance and then evapotranspiration (e.g. Lammertsma *et al.,* 2011; Keenan *et al.,* 2013) is not taken into account in the evapotranspiration equations nor later in the crop modelling. Moreover, in this study, while addressing ET_0 equation effect on crop yield projection in a climate change context, only temperatures and precipitation mean values are changed (and they are only shifted). This is a very rough inclusion of possible climate change since other climate variables (e.g. DTR, relative humidity) are likely to change and influence simulated yields via ET_0 as well. Then, differences between the yields simulated in a climate change context may have been poorly estimated when compared to what they could have been if all the climate variables had been changed.

This work has been conducted in West Africa; this area being chosen since agriculture is mainly rainfed and highly vulnerable to water availability. In other regions, the sensitivity of simulated crop yield to climate change through ET_0 formulation might be different. The extension of this study to other regions would give a more comprehensive understanding of this sensitivity of simulated crop yield changes to the ET_0 formulation and on the induced uncertainties. Although they did not consider uncertainties in crop yield changes under climate warming, Liu *et al.* (2016) illustrated clearly why a proper choice of PET methods is important for crop growth simulation on a global scale. Indeed, using the PEPIC model (grid-based EPIC model with a Python environment) to simulate crop yield of maize, they found that uncertainties derived from different PET methods on crop simulations are significant, especially for crop water use and productivity (Liu *et al.,* 2016).

5. Conclusion

This paper analyses the influence the choice of the ET_0 method has on simulated crop yield in Senegal. ET_0 and yields calculated using PM equation and *in situ* weather data are taken as baseline. It has been shown that the choice of the ET_0 method has an impact on simulated crop yield through both ET_0 %MBE and variations and that this impact depends on the climate characteristics of the station.

When *in situ* weather data are used, on average, the ET_0 and yield calculated using H equation are the closest to the ones derived using PM equation. When reanalyses and RCM climate data are used to drive ET_0 equations, ET_0 method robustness was shown to be very station dependent and, although on average over the country none of the equations singles out as the best, PM equation leads to minimized yield biases over the wettest part of the country, while H equation appears to be the most robust under dry climate. Everywhere in Senegal, ET_0 and yield derived from PT_S equation are the most sensitive to changes in temperatures and precipitation, they are followed by those calculated from PT and PM equations, Hargreaves equation leading the least ET_0 and yield sensitivity to a change in climate. The influence of the choice of the ET_0 equation becomes less important when extreme weather is reached: when there is no water and/or when the lethal temperature is reached, the evaporative demand of the atmosphere has a relatively low impact on crop.

Although this study focuses only on the Sudano-Sahelian zone climates with one crop model, its generalization to other regions and other crop models in the context of the major international effort of the AgMIP might be useful for further understanding the differences between performances of crop models and their projections of climate change impacts. In that respect, a global and multi-model analysis would allow determination of how the differences among ET equations depend on the local precipitation and temperature regimes (for instance based on the Koppen-Geiger classification, as done by Liu *et al.,* 2016) and affect the crop models' ability to simulate mean yield and variability. Being able to demonstrate that some ET equations outperform all others in an ensemble of crop models for specific climatic zones would provide a solid basis for improving models. A next step would then be to compare the response of ET_0 and yields of a variety of crop models and crops to assess if the ET_0 methods have similar effects on these different crop models or if the uncertainties in parameterizations and soil representation would blur the differences between ET_0 methods.

Acknowledgements

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Supporting information

The following supporting information is available as part of the online article:

Table S1. Empirical coefficients. Weather data = *in situ* observations.

Table S2. Regional climate models used to downscale ERA-I climate over West Africa in the ENSEMBLES project.

References

Allen RG, Pereira LS, Raes D, Smith M. 1998. *Crop evapotranspiration – guidelines for computing crop water requirements*. FAO Irrigation and Drainage Paper No. 56. Food and Agriculture Organization: Rome.

Balkovič J, van der Velde M, Schmid E, Skalský R, Khabarov N, Obersteiner M, Stürmer B, Xiong W. 2013. Pan-European crop modelling with EPIC: implementation, up-scaling and regional crop yield validation. *Agr. Syst.* **120**: 61–75. https://doi.org/10.1016/j.agsy.2013.05.008.

Barella-Ortiz A, Polcher J, Tuzet A, Laval K. 2013. Potential evaporation estimation through an unstressed surface energy balance and its sensitivity to climate change. *Hydrol. Earth Syst. Sci. Discuss.* **10**: 8197–8231. https://doi.org/10.5194/hessd-10-8197-2013.

Baron C, Sultan B, Balme M, Sarr B, Traore S, Lebel T, Janicot S, Dingkuhn M. 2005. From GCM grid cell to agricultural plot: scale issues affecting modelling of climate impact. *Philos. Trans. R. Soc. B: Biol. Sci.* **360**: 2095–2108. https://doi.org/10.1098/rstb.2005.1741.

Blaney HF, Criddle WD, U.S. Soil Conservation Service. 1950. *Determining Water Requirements in Irrigated Areas from Climatological and Irrigation Data*. U.S. Soil Conservation Service: Washington, D.C.

Bondeau A, Smith PC, Zaehle S, Schaphoff S, Lucht W, Cramer W, Gerten D, Lotze-Campen H, Müller C, Reichstein M, Smith B. 2007. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. *Glob. Change Biol.* **13**: 679–706. https://doi.org/10.1111/j.1365-2486.2006.01305.x.

Brisson N, Gary C, Justes E, Roche R, Mary B, Ripoche D, Zimmer D, Sierra J, Bertuzzi P, Burger P. 2003. An overview of the crop model STICS. *Eur. J. Agron.* **18**: 309–332.

Challinor AJ, Wheeler TR, Craufurd PQ, Slingo JM, Grimes DIF. 2004. Design and optimisation of a large-area process-based model for annual crops. *Agric. For. Meteorol.* **124**: 99–120. https://doi.org/10.1016/j.agrformet.2004.01.002.

Chiew FHS, Kamaladasa NN, Malano HM, McMahon TA. 1995. Penman-Monteith, FAO-24 reference crop evapotranspiration and class-A pan data in Australia. *Agric Water Manag* **28**: 9–21.

Christensen JH, Rummukainen M, Lenderink G. 2009. *Formulation of Very-High-Resolution Regional Climate Model Ensembles for Europe*. Met Office Hadley Centre: Exeter, UK.

Deryng D, Sacks WJ, Barford CC, Ramankutty N. 2011. Simulating the effects of climate and agricultural management practices on global crop yield. *Glob. Biogeochem. Cycles* **25**: GB2006. https://doi.org/10.1029/2009GB003765.

Dingkuhn M, Baron C, Bonnal V, Maraux F, Sarr B, Clopes A, Forest F. 2003. Decision support tools for rainfed crops in the Sahel at the plot and regional scales. In *Decision Support Tools for Smallholder Agriculture in sub-Saharan Africa : A Practical Guide*, Tjark SB, Marco W (eds). IFDC: Muscle Shoals, AL, 127–139.

Djaman K, Irmak S, Kabenge I, Futakuchi K. 2016. Evaluation of FAO-56 Penman-Monteith model with Limited data and the Valiantzas models for estimating grass-reference evapotranspiration in Sahelian conditions. *J. Irrig. Drain. Eng.-ASCE* **142**: 04016044.

Gavilán P, Lorite IJ, Tornero S, Berengena J. 2006. Regional calibration of Hargreaves equation for estimating reference ET in a semiarid environment. *Agric. Water Manag.* **81**: 257–281. https://doi.org/10.1016/j.agwat.2005.05.001.

Hargreaves GH, Samani ZA. 1982. Estimating potential evapotranspiration. *J. Irrig. Drain. Div.* **108**: 225–230.

Hargreaves GH, Samani ZA. 1985. Reference crop evapotranspiration from temperature. *Appl. Eng. Agric.* **1**: 96–99. https://doi.org/10.13031/2013.26773.

Hargreaves GH, Allen RG. 2003. History and evaluation of Hargreaves evapotranspiration equation. *J. Irrig. Drain. Eng.* **129**: 53–63.

Hoogenboom G, Jones JW, Wilkens PW, Porter CH, Boote KJ, Hunt LA, Singh U, Lizaso JI, White JW, Uryasev O, Ogoshi R, Koo J, Shelia V, Tsuji GY. 2015. Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.6 (http://dssat.net). DSSAT Foundation: Prosser, Washington.

Irmak S, Haman DZ. 2003. Evapotranspiration: potential or reference. IFAS Extension, ABE 343.

Jensen ME, Burman RD, Allen RG. 1990. Evapotranspiration and Irrigation Water Requirements. Manuals and Reports on Engineering Practice. ASCE No. 70. New York.

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ, Ritchie JT. 2003. The DSSAT cropping system model. *Eur. J. Agron.* **18**: 235–265.

Kashyap PS, Panda RK. 2001. Evaluation of evapotranspiration estimation methods and development of crop-coefficients for potato crop in a sub-humid region. *Agric. Water Manag.* **50**: 9–25. https://doi.org/10.1016/S0378-3774(01)00102-0.

Keating BA, Carberry PS, Hammer GL, Probert ME, Robertson MJ, Holzworth D, Huth NI, Hargreaves JNG, Meinke H, Hochman Z, McLean G, Verburg K, Snow V, Dimes JP, Silburn M, Wang E, Brown S, Bristow KL, Asseng S, Chapman S, McCown RL, Freebairn DM, Smith CJ. 2003. An overview of APSIM, a model designed for farming systems simulation. *Eur. J. Agron.* **18**: 267–288. https://doi.org/10.1016/S1161-0301(02)00108-9.

Keenan TF, Hollinger DY, Bohrer G, Dragoni D, Munger JW, Schmid HP, Richardson AD. 2013. Increase in forest water-use efficiency as atmospheric carbon dioxide concentrations rise. *Nature* **499**: 324–327. https://doi.org/10.1038/nature12291.

Kingston DG, Todd MC, Taylor RG, Thompson JR, Arnell NW. 2009. Uncertainty in the estimation of potential evapotranspiration under climate change. *Geophys. Res. Lett.* **36**: L20403. https://doi.org/10.1029/2009GL040267.

Knox J, Hess T, Daccache A, Wheeler T. 2012. Climate change impacts on crop productivity in Africa and South Asia. *Environ. Res. Lett.* **7**: 034032. https://doi.org/10.1088/1748-9326/7/3/034032.

Kouressy M, Dingkuhn M, Vaksmann M, Heinemann AB. 2008. Adaptation to diverse semi-arid environments of sorghum genotypes having different plant type and sensitivity to photoperiod. *Agric. For. Meteorol.* **148**: 357–371.

Kra E. 2014. FAO-56 Penman-Monteith daily from linear regression calibrated Hargreaves equation with wind terms in tropics with Limited data. *Int. J. Agron.* **2014**: e402809. https://doi.org/10.1155/2014/402809.

Kumar R, Jat MK, Shankar V. 2012. Methods to estimate irrigated reference crop evapotranspiration – a review. *Water Sci. Technol.* **66**: 525–535.

Lammertsma EI, de Boer HJ, Dekker SC, Dilcher DL, Lotter AF, Wagner-Cremer F. 2011. Global CO2 rise leads to reduced maximum stomatal conductance in Florida vegetation. *Proc. Natl. Acad. Sci.* **108**: 4035–4040. https://doi.org/10.1073/pnas.1100371108.

Liu W, Yang H, Folberth C, Wang X, Luo Q, Schulin R. 2016. Global investigation of impacts of PET methods on simulating crop-water relations for maize. *Agric. For. Meteorol.* **221**: 164–175.

Marteau R, Sultan B, Moron V, Alhassane A, Baron C, Traoré SB. 2011. The onset of the rainy season and farmers' sowing strategy for pearl millet cultivation in Southwest Niger. *Agric. For. Meteorol.* **151**: 1356–1369. https://doi.org/10.1016/j.agrformet.2011.05.018.

Oettli P, Sultan B, Baron C, Vrac M. 2011. Are regional climate models relevant for crop yield prediction in West Africa? *Environ. Res. Lett.* **6**: 014008. https://doi.org/10.1088/1748-9326/6/1/014008.

Priestley CHB, Taylor RJ. 1972. On the assessment of surface heat flux and evaporation using large-scale parameters. *Mon. Weather Rev.* **100**: 81–92. https://doi.org/10.1175/1520-0493(1972)100<0081:OTAOSH>2.3.CO;2.

Prudhomme C, Williamson J. 2013. Derivation of RCM-driven potential evapotranspiration for hydrological climate change impact analysis in Great Britain: a comparison of methods and associated uncertainty in future projections. *Hydrol. Earth Syst. Sci.* **17**: 1365–1377. https://doi.org/10.5194/hess-17-1365-2013.

Ramarohetra J, Sultan B, Baron C, Gaiser T, Gosset M. 2013. How satellite rainfall estimate errors may impact rainfed cereal yield simulation in West Africa. *Agric. For. Meteorol.* **180**: 118–131. https://doi.org/10.1016/j.agrformet.2013.05.010.

Roloff, G, Jong, R. de, Zentner, RP, Campbell, CA, Benson, VW, 1998. Estimating spring wheat yield variability with EPIC. *Can. J. Soil Sci.* **78**, 541–549.

Rosenzweig C, Jones JW, Hatfield JL, Ruane AC, Boote KJ, Thorburn P, Antle JM, Nelson GC, Porter C, Janssen S, Asseng S, Basso B, Ewert F, Wallach D, Baigorria G, Winter JM. 2013. The agricultural model Intercomparison and Improvement Project (AgMIP): protocols and pilot studies. *Agric. For. Meteorol.* **170**: 166–182. https://doi.org/10.1016/j.agrformet.2012.09.011.

Roudier P, Sultan B, Quirion P, Berg A. 2011. The impact of future climate change on West African crop yields: what does the recent literature say? *Glob. Environ. Change* **21**: 1073–1083. https://doi.org/10.1016/j.gloenvcha.2011.04.007.

Ruane AC, McDermid S, Rosenzweig C, Baigorria GA, Jones JW, Romero CC, DeWayne Cecil L. 2014. Carbon–temperature–water change analysis for peanut production under climate change: a prototype for the AgMIP Coordinated climate-crop modeling project (C3MP). *Glob. Change Biol.* **20**: 394–407. https://doi.org/10.1111/gcb.12412.

Schlenker W, Lobell DB. 2010. Robust negative impacts of climate change on African agriculture. *Environ. Res. Lett.* **5**: 014010. https://doi.org/10.1088/1748-9326/5/1/014010.

Simmons A, Uppala S, Dee D, Kobayashi S. 2007. ERA-Interim: new ECMWF reanalysis products from 1989 onwards. *ECMWF Newslett.* **110**: 25–35.

Smith B, Prentice IC, Sykes MT. 2001. Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within European climate space. *Glob. Ecol. Biogeogr.* **10**: 621–637. https://doi.org/10.1046/j.1466-822X.2001.t01-1-00256.x.

Sperna Weiland FC, Tisseuil C, Dürr HH, Vrac M, Van Beek LPH. 2012. Selecting the optimal method to calculate daily global reference potential evaporation from CFSR reanalysis data for application in a hydrological model study. *Hydrol. Earth Syst. Sci.* **16**: 983–1000.

Steiner JL, Howell TA, Schneider AD. 1991. Lysimetric Evaluation of daily potential evapotranspiration models for grain sorghum. *Agron. J.* **83**: 240. https://doi.org/10.2134/agronj1991.00021962008300010055x.

Sultan B, Baron C, Dingkuhn M, Sarr B, Janicot S. 2005. Agricultural impacts of large-scale variability of the West African monsoon. *Agric. For. Meteorol.* **128**: 93–110. https://doi.org/10.1016/j.agrformet.2004.08.005.

Sultan B, Roudier P, Quirion P, Alhassane A, Muller B, Dingkuhn M, Ciais P, Guimberteau M, Traore S, Baron C. 2013. Assessing climate change impacts on sorghum and millet yields in the Sudanian and Sahelian savannas of West Africa. *Environ. Res. Lett.* **8**: 014040. https://doi.org/10.1088/1748-9326/8/1/014040.

Thornton PE, Lamarque J-F, Rosenbloom NA, Mahowald NM. 2007. Influence of carbon-nitrogen cycle coupling on land model response to CO_2 fertilization and climate variability. *Glob. Biogeochem. Cycles* **21**: GB4018. https://doi.org/10.1029/2006GB002868.

Traoré SB, Alhassane A, Muller B, Kouressy M, Somé L, Sultan B, Oettli P, Siéné Laopé AC, Sangaré S, Vaksmann M, Diop M, Dingkhun M, Baron C. 2011. Characterizing and modeling the diversity of cropping situations under climatic constraints in West Africa. *Atmos. Sci. Lett.* **12**: 89–95. https://doi.org/10.1002/asl.295.

Van der Linden P, Mitchell JFB. 2009. *ENSEMBLES: Climate Change and Its Impacts: Summary of Research and Results from the ENSEMBLES Project*. Met Office Hadley Center: Exeter, UK 160 pp.

Williams JR. 1990. The erosion-productivity impact calculator (EPIC) model: a case history. *Philos. Trans. R. Soc. Lond. B: Biol. Sci.* **329**: 421–428.

Yoder RE, Odhiambo LO, Wright WC. 2005. Evaluation of methods for estimating daily reference crop evapotranspiration at a site in the humid southeast United States. *Appl. Eng. Agric.* **21**: 197–202.

Zarei AR, Zare S, Parsamehr AH. 2015. Comparison of several methods to estimate reference evapotranspiration. *J. Appl. Ecol.* **23**: 17–25.