Climatic Change (2011) 104:755–782
DOI 10.1007/s10584-010-9874-x

Including tropical croplands in a terrestrial biosphere model: application to West Africa

**Alexis Berg · Benjamin Sultan ·
Nathalie de Noblet-Ducoudré**

Received: 18 December 2008 / Accepted: 10 February 2010 / Published online: 26 June 2010

Abstract Studying the large-scale relationships between climate and agriculture raises two different issues: the impact of climate on crops, and the potential feedbacks to climate from croplands. A relevant and consistent framework to address this twofold issue is to extend existing Dynamic Global Vegetation Models, which can be coupled to climate models, in order to explicitly account for croplands. Here we present the first results of such a strategy applied to tropical croplands over West Africa. We introduce into the terrestrial biosphere model ORCHIDEE (IPSL) adequate processes and parameterisations taken from the crop model SARRAH (CIRAD), which is calibrated for millet over this region. The resulting model, ORCH-mil, realistically simulates the growth and yield of millet when tested on an experimental station in Senegal. The model is then applied over West Africa using a 36-year climate reanalysis dataset. First the model is tested in terms of yield simulation, against national millet yields from the FAO database. The ability of the model to reproduce the spatial and temporal variability of millet yields is assessed. Then, the effects on land surface fluxes of explicitly accounting for croplands are examined: significant differences between ORCH-mil and ORCHIDEE appear, through changes in sensible and latent heat fluxes, surface albedo, and water resources. These differences encompass a potential impact on the monsoon system, mainly during the retreat of monsoon rains.

A. Berg · B. Sultan
Laboratoire d'Océanographie et du Climat: Expérimentation et Approches Numériques,
Institut Pierre Simon Laplace (LOCEAN / IPSL), Paris, France

A. Berg · N. de Noblet-Ducoudré
Laboratoire des Sciences du Climat et de l'Environnement,
Institut Pierre Simon Laplace (LSCE / IPSL), Gif-sur-Yvette, France

A. Berg (✉)
LOCEAN/IPSL, Université Pierre et Marie Curie, Boite 100, T45/55, 4 Place Jussieu, 75252
Paris cedex 05, France
e-mail: alexis.berg@locean-ipsl.upmc.fr

1 Introduction

Studying the relationships between climate and agriculture raises two different issues.

First, agricultural production is highly vulnerable to climate, and can be considered as the most weather-dependant of all human activities (Oram 1989; Hansen 2002), with socio-economical impacts whose severity varies from one region to another (Ogallo et al. 2000). These impacts are particularly strong in developing countries in the tropics with low levels of crop management technology. In many cases they are exposed to high variability in climate like monsoon systems over West Africa or India, or the El Niño-Southern Oscillation (ENSO) influence over the American continent (Challinor et al. 2003). Thus, it is crucial to increase our understanding of how crop production responds to seasonal and interannual climate variability; and it is essential that this analysis take place on a scale consistent with climate model outputs, so as to be able to make use of climate predictions—particularly in the context of a changing climate. This large-scale response, typically on a regional scale, is also the one needed for support to decision makers and agricultural planning.

On the other hand, on a regional or a global scale, agriculture plays a role in the climate system: it alters carbon and water budgets, and affects the surface energy balance (Feddema et al. 2005). Indeed, croplands account for 12% of the global land surface (Ramankutty et al. 2008); when including pastures and rangelands, nearly 50% of the potentially vegetated land surface has been affected by agriculture (Foley et al. 2005). Croplands differ from natural vegetation regarding phenology (sowing, harvest) and land management (irrigation, fertilization, tillage…). This human management modifies the biogeochemical cycles and alters the land surface biophysical properties (roughness, albedo), thus causing feedbacks to the climate (Boucher et al. 2004; de Noblet-Ducoudré et al. 2004).

A relevant framework to address this twofold issue is the extension of existing Dynamic Global Vegetation Models (DGVMs), originally designed to account for interactions between the atmosphere and the land surface, to include a representation of croplands (Betts 2005; Pielke et al. 2007). So far, few terrestrial biosphere models have included detailed representations of managed ecosystems: Kucharik and Brye (2003) have added crop process modules to the land biosphere model IBIS (Foley et al. 1996) to simulate the impacts of climate and land management on crop production and biogeochemistry in the US corn belt (Donner and Kucharik 2003); Osborne et al. (2007) have included the large-scale agronomic model GLAM (Challinor et al. 2004) into the land surface component of the UK Met Office climate model HadAM3; and Bondeau et al. (2007) have added several crop functional types into the LPJ-DGVM (Sitch et al. 2003) to simulate yields of the major crops worldwide and analyse the role of agriculture on the 20th century global terrestrial carbon balance. Despite these recent advances, however, realistically accounting for the variety of croplands globally in a coupled land/atmosphere model remains a challenge for the Earth System modelling community.

The objective of this paper is to propose a preliminary approach to include tropical croplands in a DGVM that can either be used off-line, as a diagnostic or impact tool, or on-line, that is coupled to a global atmosphere–ocean model. To start with, we have worked on millet crop in West Africa. West Africa is a region which well illustrates the two-way influence between climate and agriculture, since the latter is almost entirely rain-fed and highly dependant on the fluctuations of the West African Monsoon (WAM; Sultan et al. 2005; Baron et al. 2005). Developing a tool which simulates the large-scale response of crops to this regional climate variability is then of great interest to analyse and predict the impacts on food production and security, in the only region worldwide where agricultural production per capita has decreased over the last 40 years (Dyson 2001). On the other hand, surface characteristics play an important role in the WAM precipitation variability on seasonal, inter-annual and decadal time scales. Although Atlantic oceanic forcing is the dominant driver of WAM variability (e.g., Giannini et al. 2003), several modelling studies have shown that the twentieth century drought in West Africa is most likely to have been amplified by human-induced land use/land cover changes, and by the regional climatic feedback due to the vegetation dynamics and soil moisture (see for instance Zheng and Eltahir 1997, 1998; Wang and Elathir 2000; Foley et al. 2003; Wang et al. 2004). Thus, improving simulations of managed ecosystems in West Africa might help to analyse the impact of land-use on the monsoon system.

We present an original methodology to include millet crop into the DGVM ORCHIDEE (Organizing Carbon and Hydrology in Dynamic Ecosystems; Krinner et al. 2005) which is the land surface model developed by the IPSL institute (Institut Pierre-Simon Laplace). In its original version, ORCHIDEE crudely accounts for croplands as simple grasslands with enhanced photosynthetic capacities. A new version of this model has recently been developed in order to improve the representation of croplands for developed countries in temperate regions (Gervois et al. 2004). In this version, ORCHIDEE assimilates daily outputs from the generic crop model STICS (Brisson et al. 2003), for variables which are either badly simulated (e.g. Leaf Area Index) or missing (e.g. nitrogen stress). However, so far STICS has not been calibrated to simulate tropical crops; the resulting ORCHIDEE-STICS model is only designed for temperate C3 and C4 crops, such as wheat and maize, allowing studies over regions such as Europe (Smith et al. 2010). Moreover, although the assimilation method adopted for this version allowed taking advantage from further improvements in STICS with minimum adjustments in ORCHIDEE, it also implies redundancies in the computation of carbon and water budgets, which may generate inconsistencies in case of divergence between the two computations. Thus, in our case the approach we choose in order to improve the representation of tropical crops in ORCHIDEE is to include directly, in the standard version of ORCHIDEE, specific processes and parameterisations taken from an existing crop model already well calibrated and validated for millet over the West African region. The model we derive these parameterisations from is named SARRAH and has been developed by the CIRAD (French Agricultural Research Centre for Agricultural Development; Dingkuhn et al. 2003). We will refer to the resulting model as ORCH-mil. It is presented herein and we show (1) its ability to capture the relationship between climate and crop productivity and to simulate crop yields at a regional scale, (2) how explicitly accounting for croplands in ORCHIDEE modifies the biophysical properties of the land surface and the fluxes of heat and water vapour exchanged at the land/atmosphere interface.

In a first section we present the models and data used in our study. A second section describes the developments from ORCHIDEE to ORCH-mil, which is tested over one typical semi-arid location in Senegal. ORCH-mil is then applied over a large regional window of West Africa: the third section compares simulated yields with national census data from the FAO (Food and Agriculture Organization). The last section analyses the modifications of the land surface energy budget induced by an improved representation of croplands. The conclusion sums up the main results and discusses the future development priorities and challenges.

2 Materials and methods

2.1 ORCHIDEE (Organizing Carbon and Hydrology in Dynamic Ecosystem)

ORCHIDEE (Krinner et al. 2005) is the dynamic global vegetation model developed at IPSL (Institut Pierre-Simon Laplace). It simulates water, carbon (C) and energy exchanges between the land surface and the atmosphere. It is designed to be coupled to a global climate model, in order to allow analysis of vegetation and land-use feedbacks on climate. In a more simple way, it can also be used “off-line” (i.e. forced by meteorological data) to assess the impact of climate on ecosystems: Ciais et al. (2005), for example, showed that ORCHIDEE reasonably simulates the response of natural ecosystems in Europe to a climatic anomaly such as the 2003 heat wave.

ORCHIDEE consists of three main modules:

- The Soil–Vegetation–Atmosphere Scheme SECHIBA (Ducoudré et al. 1993; De Rosnay and Polcher 1998) which simulates biophysical exchanges of water and energy between land surface and atmosphere on a short time-scale (half-an-hour). It computes fluxes of momentum, heat, water, and canopy C exchanges, as well as soil water budget and surface energy budget.
- The biogeochemical model STOMATE which describes seasonal C and vegetation dynamics on a daily basis: for instance phenology, C allocation, litter production and decomposition, senescence. This module provides SECHIBA with the physical description of vegetation necessary to compute fluxes (e.g., Leaf Area Index (LAI)). In return it receives the environmental and climatic stresses that affect vegetation development. Note that plant transpiration, respiration and assimilation are computed in SECHIBA since these processes have to be computed at the shortest time-scale.
- A module taken from the Lund–Postdam–Jena (LPJ) model (Sitch et al. 2003) describing the dynamics of the potential natural vegetation (i.e. long-term evolution of vegetation from one type to another). It includes rules of interspecies competition for light, role of fire, appearance and disappearance of different plant types, etc. Time-step here is generally 1 year. This module can be turned off and vegetation distribution prescribed, or read on a land-cover map.

To account for global vegetation, ORCHIDEE in its standard version uses 10 natural plant functional types (PFTs) (eight evergreen and deciduous trees, C3 and C4 grasses). Two additional PFTs are designed, so as to account for C3 and C4 crops: in the standard version these crops are crudely modelled as, respectively, C3 and C4 grasslands, with enhanced assimilation rates. The global land surface is divided into grid cells, which size is not prescribed but depends on the grid size of climate input. Several PFTs can coexist within the same grid box (but there is no spatial repartition within the cell). They all share the same climate forcing but fluxes are computed separately for each PFT depending on their own properties. Fluxes are then averaged before entering the first atmospheric level: thus the vegetation feeds back on the atmosphere.

2.2 SARRAH

SARRAH (Dingkuhn et al. 2003) is a crop modelling platform developed on the basis of SARRA, the water balance model frequently used by agronomists and agrometeorologists working in the Sahel (zoning and risk-analysis: Affholder 1997; Baron et al. 1999, yield forecasting: Samba 1998). SARRAH based models typically simulate attainable yields at field scale. Extrapolation from plot to region is routinely done by Agrhymet (Niamey, Niger; see http://www.agrhymet.ne) for agro-meteorological forecasting using the DHC system, which includes SARRA as a component (Samba 1998; Samba et al. 2001). The version of SARRAH calibrated for millet was structured to enable such applications as well, but with greater physiological details. It combines a water use efficiency approach—with daily simulation of water run-off and infiltration, soil evaporation and ground cover transpiration, fraction of transpirable soil water—and a radiation use efficiency approach to simulate C assimilation and partitioning according to allometric rules (see Baron et al. 2005 for further details on the model). The crop cycle length depends on fixed thresholds of thermal time. SARRAH has been calibrated and validated on several independent experimental datasets for field grown millet in Senegal (Baron and Sarr, unpublished data; Sultan et al. 2005; Baron et al. 2005).

2.3 Climate data

2.3.1 The NCC atmospheric forcing

NCC is a large-scale atmospheric forcing dataset (Ngo-duc et al. 2005) specifically designed to force land surface schemes, and that is now being used in a number of intercomparison projects (e.g. ALMIP, de Rosnay et al. 2009). The dataset is built on NCEP/NCAR reanalysis (National Centre for Environmental Prediction/National Centre for Atmospheric Research) corrected by observational data from CRU (Climate Research Unit; New et al. 1999, 2000). The variables in the meteorological data are divided into two types: state variables (near-surface air temperature, specific humidity, wind speed and surface pressure) and flux fields (radiation and precipitation). The data construction involves two steps: interpolation of the NCEP/NCAR Reanalysis data to a grid of $1° \times 1°$ and correction of reanalysis data with the observationally based data. NCC extends from 1948 to 2000 with a spatial resolution of $1° \times 1°$ and a 6-hourly temporal resolution. The NCC data set was validated by comparing discharges of the world's largest rivers simulated by ORCHIDEE forced with different meteorological data. It has proved to be very useful in the study of the evolution of continental water storage during the past 50 years (see Ngo-duc et al. 2005).

2.3.2 The Bambey synoptic station

The daily climate data from the synoptic station (measuring global radiation, insolation, surface wind speed, humidity and temperature) and the rain gauge in Bambey

National Research Station (BNRS) has been used to calibrate and validate the crop model SARRAH. It is a typical Sahelian location (16.5°W–14.7°N) in Senegal with an annual rainfall amount varying typically between 350 and 650 mm per year. Two years of daily data were available: 1996 and 1997. The two models SARRAH and ORCHIDEE were forced with this climate input. However, whereas SARRAH can use data from the local weather station at a daily time step, ORCHIDEE needs data at the half-hourly time step. Thus BNRS data needed to be disaggregated. For this we extracted the 1996 and 1997 NCC (see previous sub-section) data for the $1° \times 1°$ grid-cell corresponding to Bambey and applied the NCC diurnal cycle to the BNRS daily values. We obtained 6-hourly data that were further interpolated by ORCHIDEE at the half-hourly time-step. This has been done for radiation and temperature; for rainfall, we used satellite imagery. Rainfall probability computed every 15 min using data from Meteosat-Second-Generation for the year 2004 was used to estimate a typical hourly distribution of rainfall. This distribution has then been applied to disaggregate 1996 and 1997 BNRS daily values. Thus, ORCHIDEE is forced with a 6-hourly-disaggregated BNRS dataset.

2.4 Crop data

2.4.1 The Bambey National Research Station

Measurements of biomass, grain production and LAI are available for the BNRS in Senegal for two consecutive years 1996–1997 and several water irrigation regimes, including rain-fed situations. These data have been initially used to calibrate and validate the crop model SARRAH. Both biomass and grain production were simulated satisfactorily by the model (Sultan et al. 2005; Baron et al. 2005). We will thus use the SARRAH simulations as a proxy of these data.

2.4.2 The Agrhymet survey

Long-term means (1971–2000) of sowing dates and millet yields have been computed by the regional centre Agrhymet: a water budget model is forced by rainfall observations on a 0.5 degree scale; results are then empirically converted into yields values by statistical relationships based on on-farm observations. Sowing dates are computed according to a rainfall threshold method, and validated by local observations as well.

Thus, this is a model-based product but corrected and validated by in-situ observations (Samba 1998; Samba et al. 2001): in the absence of any reliable spatialized data for yields and sowing dates, it can be considered as a good approximation to on-farm reality.

2.4.3 The FAO statistics

The Food and Agriculture Organization of the United Nations (FAO) compiles data annually on various agricultural production statistics of its member nations. This is, to our knowledge, the only source available for long time series analysis of cross-national agricultural data. For West African countries, the FAO on-line database (http://faostat.fao.org/) contains annual agricultural statistics from 1961 to present: for millet, average yields, harvested area and total production are reported. This allows us to test the yields simulated by our model on a national scale, over the 1965–2000 period.

However, one must remember that the FAO data are a compilation of results reported by member nations, rather than direct observations. Consequently, such data can often be biased by under or over-reporting of agricultural production, or because poor countries do not have the resources or infrastructures to conduct rigorous surveys (Ramankutty 2004). In West Africa, given the lack of resources and infrastructures, and the numerous civil wars or political instabilities that took place in various countries since the 60’s, the quality of the statistics must be considered carefully. Moreover, yield data may show trends unrelated to climate. Figure 1 shows FAO millet yields from 1965 for several of the most important millet producing countries in West Africa: it is striking that some countries show increasing yields over time (Burkina-Faso, Senegal), when others face decreasing values (Chad, Niger). While local climate fluctuations may play a role in these trends (for example, rainfall recovery since the early 90’s), non-climatic factors are likely to be the dominant drivers. Explaining the causes of these trends is nevertheless not straightforward. Positive trends in developed countries are usually attributable to the intensification of agriculture (i.e., the use of improved varieties, fertilizers and chemicals, mechanization), but agricultural practices in West Africa have not significantly intensified over recent decades. Land-degradation, intra or extra-national migrations, economic crisis, etc. may also have significant impact on national yields evolution. Because these potential non-climatic effects will not be simulated by any climate-driven-only crop model, one needs to detrend observations when analysing interannual

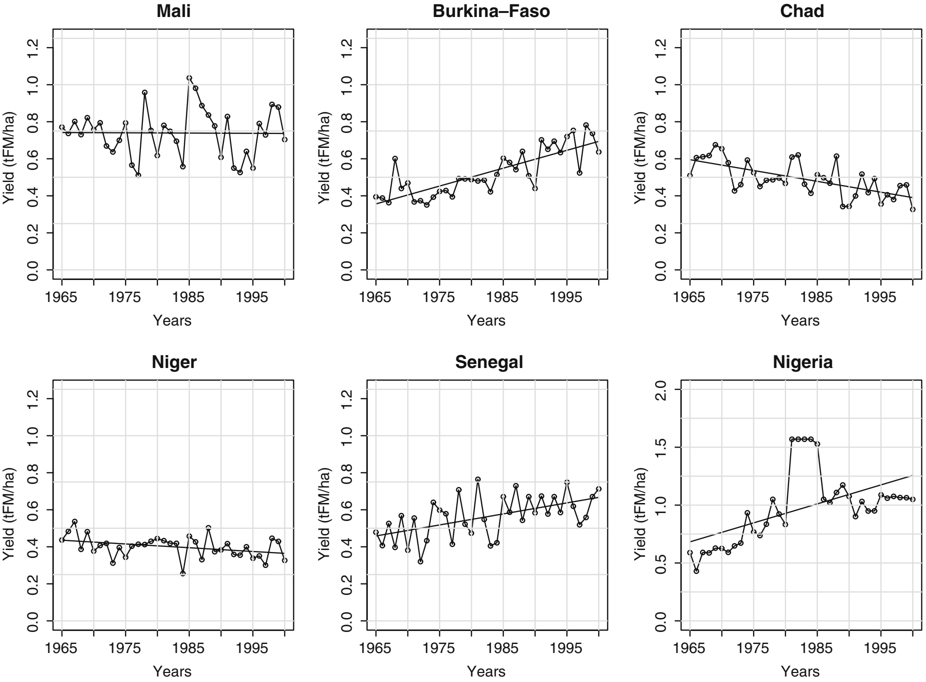

Fig. 1 National millet yields (in tons of fresh matter per hectare) from 1965 to 2000 for several West African countries, as given by the FAO database. *Dashed lines* show linear trends that will be removed to compute detrended standardized anomalies

variability. It will be done in this study very simply by removing the linear trend (y = at + b, which are shown on Fig. 1) from each time series. Since sorting out climatic and non-climatic effects is not possible, this might also remove potential climate-driven trends. As in such a case simulated yields would show a trend as well, detrending observations also implies to detrend simulated yields before comparing them to observations; finally it also implies to detrend climate data when analyzing climate/yield relationship.

3 From ORCHIDEE to ORCH-mil

3.1 ORCHIDEE first guess

Our first step is to compare the outputs of ORCHIDEE and SARRAH for the same location in West Africa and the same year: the BNRS in 1997. Both models are forced with the same climate input (see Section 2.3). Regarding soil structural parameters, SARRAH uses a sandy soil, whereas ORCHIDEE uses the same mean type of soil with average characteristics as it always does. This is not satisfactory, but improving ORCHIDEE's ability to describe soil diversity was not the purpose of this study. The same observed sowing date is prescribed in both simulations, July 19th.

Figure 2 compares the outputs from both models in terms of LAI and biomass (total and compartmental biomasses). Because ORCHIDEE represents millet as a

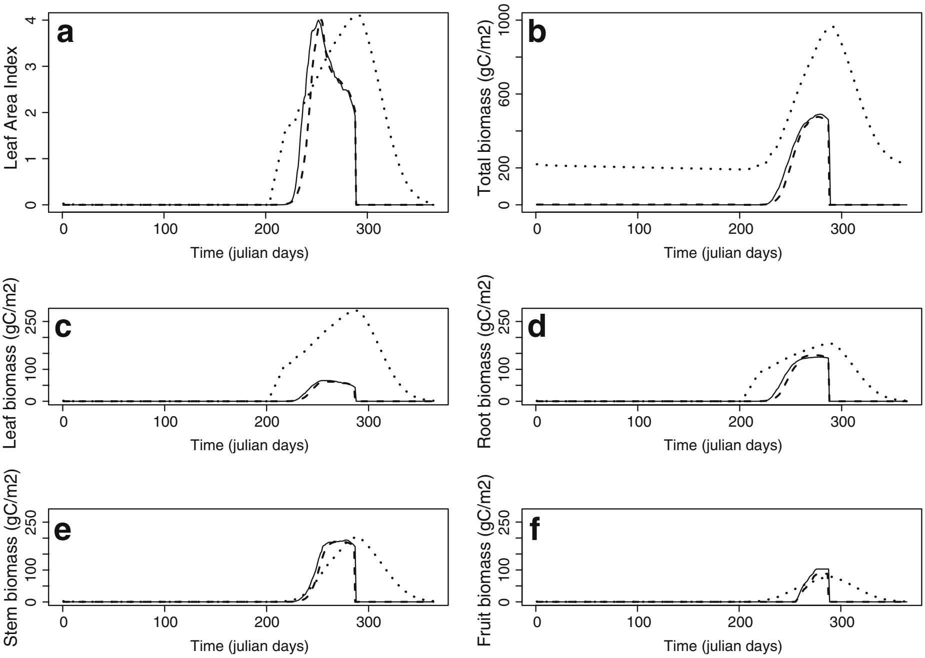

Fig. 2 Comparison between standard version of ORCHIDEE (*dotted line*) and SARRAH (*full line*) for simulations of **a** Leaf Area Index, **b** total biomass, **c** leaf biomass, **d** root biomass, **e** stem biomass, and **f** fruit biomass, for year 1997 in Bambey, Senegal (biomasses are in grams of carbon per square meter). *Dashed lines* show the same simulation by ORCH-mil

natural C4 grass with enhanced photosynthesis, the cycle is too long, mainly due to the absence of harvest. Moreover, growth at the beginning of the cycle is too quick: in ORCHIDEE, growth starts immediately after sowing and is linear. ORCHIDEE does not simulate the long exponential development of the plant at this early stage. This immediate growth results from the presence of a "reserve" carbon pool in the model, which can be seen on the "total biomass" graph (Fig. 2b): the reserve remains full during the dry season (the steady 200 gC/m^2 line), and is used by the plant to grow rapidly at the beginning of the rainy season—and finally is filled up again, until next cycle. This storage ability, initially designed for "tree" and "perennial grass" PFT in ORCHIDEE, is clearly unrealistic for annual grasses.

Total biomass in ORCHIDEE is too large, mainly because of this reserve pool and because of the overestimation of leaf biomass (Fig. 2c). The low prescribed Specific Leaf Area (SLA) value allows the LAI maximum value to be close to the one given by SARRAH (LAI = SLA × leaf biomass). However, this constant SLA implies that LAI in ORCHIDEE is directly proportional to leaf biomass. The resulting LAI dynamics can not, then, match that of SARRAH, in which SLA is more realistically parameterised as a function of leaf growth rate and implies a more complex LAI dynamics.

3.2 ORCH-mil

In order to turn ORCHIDEE's "super-grassland" into a realistic tropical cropland PFT, we suppress the reserve pool, and we include SARRAH's carbon allocation scheme, as well as SLA parameterisation. We make the assumption that it is not necessary to bring complex modifications upstream to the C and water budgets. Only allocation dynamics will be changed, thus implying modifications only in the STOMATE part of ORCHIDEE (see Section 2.1). This approach of "minimum change" is generally the one adopted by vegetation modellers who wish to account for croplands in global land surface schemes (Scholze et al. 2005). As 2 years of BNRS data are available (1996–1997), all changes in ORCHIDEE are done in order to match the 1997 outputs of SARRAH, and the year 1996 is kept unseen by the model, as an independent validation dataset.

Hereafter we present the details of our model for which modifications in ORCHIDEE were necessary. For further description of unmodified ORCHIDEE's parameterisations (e.g., soil carbon or water dynamics), please see Krinner et al. (2005) and references herein.

3.2.1 Growth and development

The crop can either be sowed on a prescribed date, or sowed depending on a rain criterion in order to approximate farmer's decision. Sowing biomass is prescribed.

The millet cycle is divided into six different stages. Harvest takes place at the end of the last stage. The length of these stages is prescribed as a sum of growing degree days (gdd) to be reached. Thus, a gdd counter is added to ORCHIDEE: thermal time, for a day j after the beginning of the crop cycle, is given by:

$$GDD_j = \sum_{i=S}^{j} (\min(Topt, T_i) - Tb)$$

where S is the date of the beginning of the crop cycle, Topt is a temperature above which additional heat is inefficient (30°C), Tb the base temperature below which development ceases (11°C); T_i is the mean air temperature of day i provided by the climate forcing.

Stages 1 to 3 are vegetative stages, stage 4 is the floral stage, stage 5 grain filling, and stage 6 mere senescence. Each day during stage 1 to 4, total biomass is partitioned between roots, stems and leaves according to empirical, allometric rules (Samba et al. 2001):

$$
\begin{aligned}
BMabg &= Bmtot * (a * BMtot + b)\\
BMleaf &= BMabg * (a' * BMabg + b')\\
BMroot &= BMtot - BMabg\\
BMstem &= BMabg - BMleaf
\end{aligned}
$$

where BMtot, BMabg, BMleaf, BMroot, BMstem, are, respectively total, above-ground, leaf, root and stem biomasses (in gC/m^2). a, a', b, b', are empirical parameters, respectively 4.44×10^{-2} m^2/gC, -2×10^{-3} m^2/gC, 0.5 and 0.63.

Note that the "Reserve" pool no longer exists. No biomass is allocated to the fruits during these 4 first stages.

Biomass produced during stage 4 (floral stage) determines the "grain sink" that is, the maximum yield that the plant can reach at the end of the growing season. Any stress occurring during that stage therefore reduces this potential yield.

$$PotY = K * (BM_{e4} - BM_{i4}) + C$$

where BM_{e4} and BM_{i4} are respectively total biomasses at the end and at the beginning of stage 4, and PotY is potential yield (i.e., grain sink). K and C are parameters, respectively 0.35 and 45 gC/m^2.

This grain sink is filled during stage 5: allocatable biomass is then allocated in priority to the "fruit" carbon pool. Each day a part of this sink is filled, depending on current water stress. For one day in stage 5:

$$DayY_i = PotY * \left(\frac{(T_i - T_b)}{GDD5}\right) * Wl$$

$$\text{And: } BMfruit_i = BMfruit_{i-1} + DayY_i$$

where $DayY_i$ is the biomass allocated to the "Fruit" pool on day i, T_i is the mean temperature of the day and GGD5 the sum of growing degree days necessary to complete stage 5. Final yield is BMfruit at the end of stage 5. Wl is a drought reduction term: in SARRAH, it is given by Tr/TrPot (ratio of real plant transpiration to potential transpiration as defined by plant development and climate evaporative demand); however, ORCHIDEE computes no plant potential transpiration. Hence, in our version Wl is given by Ev/EvPot (ratio of actual evapotranspiration to potential evapotranspiration), which can be considered as close enough to Tr/TrPot in the end of the crop cycle, since soil evaporation becomes less important due to radiative shading by foliage density.

Thus, if no water stress occurs during stage 5, final yield reaches potential yield. Grain filling also induces leaf senescence if sink capacity exceeds current assimilation rate: missing biomass is then taken mainly from leaves, and also from stems. Half of this biomass is lost during this translocation process, so as to account for an energetic cost. This detailed grain filling scheme allows for variable harvest indexes. Note that neither SARRAH nor ORCHIDEE includes, so far, any representation of nitrogen stress: thus in ORCH-mil millet is not nitrogen-limited.

Stage 6 is mere senescence: the plant dries up, until harvest at the end of the stage. In the present version of ORCH-mil all the biomass then goes into litter; but a separate parameterisation for grains will be designed in the near future since that carbon pool returns to the atmosphere with a different time constant.

3.2.2 SLA and LAI

The SLA parameterisation used to convert leaf biomass into LAI depends on leaf growth rate and on genetic minimum and maximum values (Penning de Vries et al. 1989):

$$SLA_j = \min(SLA_{\max}, \max(SLA_{\min} Z_j))$$

where

$$Z_j = SLA_{j-1} - A * (SLA_{j-1} SLA_{\min}) * \left(\frac{(BMleaf - DayBMleaf)}{BMleaf}\right) + SLA_{\max} * \left(\frac{DayBMleaf}{BMleaf}\right)$$

where DayBMleaf is the daily increment of leaf biomass. Maximum and minimum SLA values are 1.44e–01 and 4.44e–02 m^2/gC. A is 0.2.

LAI is then classically given by SLA * BMleaf. This parameterisation, instead of a constant prescribed value, allows for a more detailed representation of the existing relations between leaf growth and LAI: SLA is stronger for young thin leaves, and decreases as they get older and thicker.

3.2.3 Respiration and senescence

ORCHIDEE and SARRAH do not represent senescence similarly. In SARRAH, respiration is only maintenance respiration, which depends on temperature and biomass (Penning de Vries et al. 1989): at the end of the crop cycle, respiration is stronger than Gross Primary Production (GPP), resulting in a negative Net Primary Production (NPP). In other words, there is a short period of senescence, before harvest, during which this negative NPP drives a loss of biomass.

Conversely, respiration in ORCHIDEE is predominantly growth respiration, as a constant “tax” on allocatable biomass. Maintenance respiration, depending on biomass and temperature (following Ruimy et al. 1996), is comparatively much weaker (for C4 grasses). Thus, GPP is almost always stronger than total respiration (the sum of maintenance and growth respirations), and NPP is almost never negative. Plant senescence, i.e. loss of biomass, is driven by other parameterisations depending on climatic conditions: temperature, humidity.

Because we compute a rainfall-based sowing date and prescribe a fixed cycle duration, it is not relevant to keep a climatic-driven senescence in ORCH-mil: the timing of the different phases of the plant cycle in the model are not related to climatic conditions (other than temperatures sums). Thus, we are led to modify respiration in ORCHIDEE: growth respiration is suppressed, and maintenance respiration is enhanced (the formulation remains unchanged but parameters are set to higher values), so that the respiration/senescence representation in ORCH-mil is similar to that of SARRAH.

3.2.4 Photosynthetic capacities

As mentioned above, we do not modify the photosynthesis parameterisation: carbon assimilation in our new version still follows Collatz et al. (1992), a coupled photosynthesis-stomatal conductance model for C4 plant. Indeed, this formulation yields similar GPP values as the formulation in SARRAH—which is based on the conversion of photosynthetically efficient radiation into dry matter (Sinclair and Mudchow 1999)—and in addition allows to account for future differences in atmospheric CO_2 concentration.

However, we slightly modify a specific parameter: the assimilation maximum rate Vcmax (maximum rate of Rubisco carboxylation): its maximum value is reset to 80 μmol s^{-1} m^{-2}, instead of 100 in the former “super productive grassland” parameterisation; moreover, a linear decrease in stage 5 and 6 is prescribed, respectively from 100% to 70% of the maximum value and from 70 to 40%. This linear trend accounts for a decrease in photosynthesis capacities with older leaves. ORCHIDEE supposedly already accounted for decreasing photosynthetic capacities through a parameterisation of leaf age; but the allocation scheme we introduced made it impossible to rely on the computed leaf age any more. Thus, we parameterise the same decreasing trend for Vcmax as the one affecting radiation conversion efficiency in SARRAH.

The new version ORCH-mil resulting from the above modifications is calibrated on Bambey for 1997. The outputs are shown on Fig. 2 in dashed lines: ORCH-mil matches SARRAH (and thus, the observations) very accurately.

3.3 Site evaluation of ORCH-mil in Senegal

Since the calibration and parameterisation phase has been done in regard to the 1997 BNRS data, a validation exercise can be built in by forcing ORCH-mil with climate data over the same location but for 1996, a year unseen by the model in the calibration section. Figure 3 shows the same comparison as Fig. 2, but for 1996.

ORCH-mil matches SARRAH reasonably well. Remaining discrepancies mainly result from differences in soil water and water stress parameterisation, which we did not modify. Indeed, an under-reaction to water stress appears around day 260: ORCH-mil biomass is not enough impacted by a dry spell occurring during stage 5, and the supplementary biomass is allocated to stems. This mismatch however remains acceptable. On the two available years of BNRS data (96 and 97), it can thus be considered that ORCH-mil overall realistically represents millet when compared to SARRAH. However, this remains a limited and preliminary test, and ORCH-mil should be further tested on other experimental sites in West Africa where in situ measurements are available.

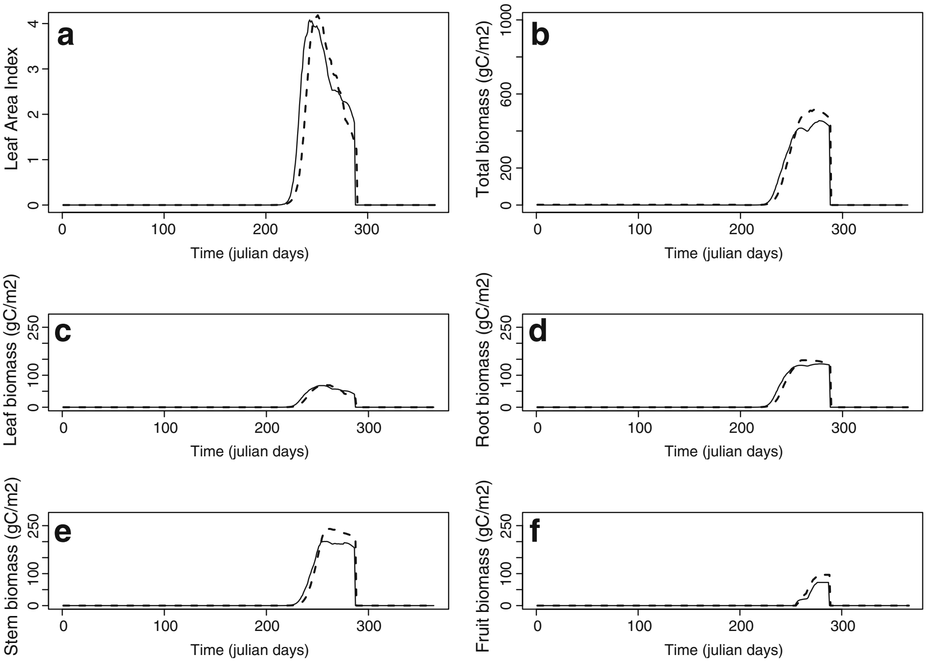

Fig. 3 Comparison between ORCH-mil's (*dashed line*) and SARRAH's (*full line*) simulations of **a** Leaf Area Index, **b** total biomass, **c** leaf biomass, **d** root biomass, **e** stem biomass, and **f** fruit biomass, for year 1996 in Bambey, Senegal (biomasses are in grams of carbon per square meter)

4 Simulation of yields over West Africa

4.1 ORCH-mil at regional scale

We now run the model on a regional scale. We force ORCH-mil with the NCC climate data from 1965 to 2000 over a regional window of West Africa (9°N–20°N; 20°W–24°E—see Fig. 4) broadly corresponding to the zone suitable for millet production. Since millet production in West Africa is entirely rain-fed, we do not use the irrigation module of ORCHIDEE (de Rosnay et al. 2003).

Millet is simulated everywhere across the simulation domain. However, simulated yields are to be compared to FAO observations, which, as mentioned in Section 2.4, are given as country averages. It is thus necessary to aggregate simulated yields from the $1^\circ \times 1^\circ$ scale to the country level. In order to make a realistic comparison to observations, one must account for the observed millet spatial distribution in the aggregation. Combining national, state, and county level census statistics with a global data set of croplands, Monfreda et al. (2008) built global distribution maps for most of the crops (175) grown around the world, at a 5 min resolution. We use the map they provide for millet, over West Africa (Fig. 4). Although this map is only supposed to describe the current (circa year 2000) situation, we use it for the whole simulation time period, for we are aware of no similar explicit millet map going back into recent decades. FAO data indicate that the total millet area in Mali and Burkina-Faso has nearly doubled from 1960 to present, and quadrupled in Niger. Hence, the assumption we make here is that although the crop fractions increased locally, the

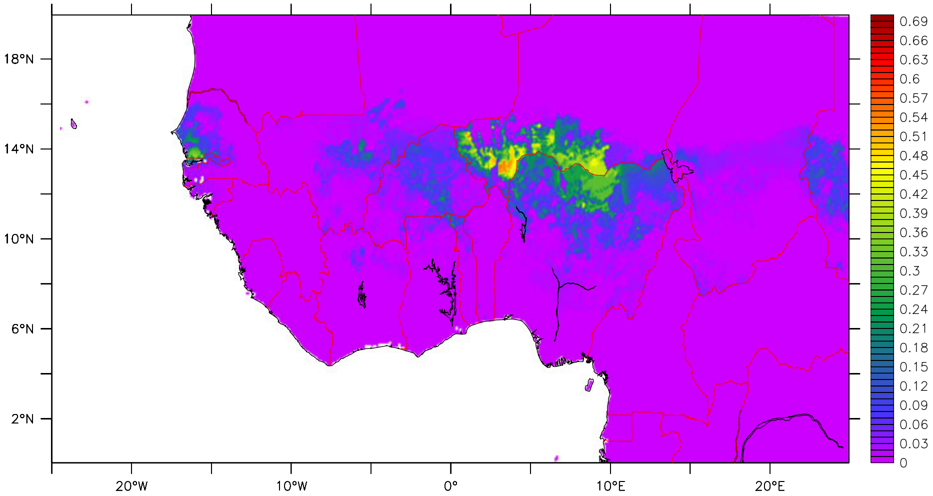

Fig. 4 Millet spatial distribution (in pixel fractions) over West Africa. Redrawn from Monfreda et al. (2008)

general pattern of millet cultivation and the relative weight of the different regions within one country remained broadly constant.

Yields per country are then derived by weighing the pixels of each country by their crop fraction. Similarly, we also aggregate rainfall as provided by the NCC climatology to derive the "national" rainfall. The countries considered in this study are Mali, Niger, Burkina-Faso, Senegal and Chad. Although a large millet producer, according to Fig. 4, we do not consider Nigeria in our analysis, as FAO data for this country shows major shifts (Fig. 1) which hampers comparison to simulations.

Two types of millet are used, with different cycle lengths. GDD requirements for the different stages of each cultivar are given in Table 1. Given average temperatures in the region, the first one approximately corresponds to a 90-day cultivar, appropriate for short rainy seasons in the Sahelian region; the second one to a 120-day cultivar, more appropriate for the longer rainy seasons in the sahelo-soudanian region. Note however that because of the dependence of cycle length on sums of temperature, a prescribed GDD requirement still leads to a latitudinal gradient of crop cycle duration. We run two separate 36-year regional simulations, one for each type of millet, 90-day and 120-day. We choose the most appropriate one per country *a posteriori*, selecting the one that best fits with observed data. Each simulation starts with a 15-year spin-up run forced with the climate observed in 1965, to initialize soil water conditions (since the model starts with soils at field capacity at all grid points).

Table 1 GDD requirements (in sum of °C day) for the different crop cycle stages in ORCH-mil, for the 90-day (left) and 120-day (right) cultivars

Stage 1	50	50
Stage 2	410	710
Stage 3	30	30
Stage 4	470	570
Stage 5	400	500
Stage 6	200	200
Total	1,560	2,060

4.1.1 Sowing dates

In order to apply ORCH-mil at the regional scale, it is necessary to parameterise the sowing date. Indeed, a single sowing date can not be prescribed over the whole region: we have to account for the south–north gradient in the planting date, which reflects the south–north gradient in the onset of monsoon rains. Based on a rain-threshold approach, derived from farmers' strategy (Ati et al. 2002; Sultan et al. 2005) the following methodology, is adopted:

- A planting window is prescribed, outside which sowing is not allowed (from early May to the end of August)
- Until day 180 (end of June), the sowing date is defined as the first day with either more than 20 mm of rain in 1 day, or 30 mm in two or three consecutive days.
- After day 180, criteria become less restrictive: the crop season begins when three consecutive rainy days occur, with a total sum of more than 10 mm.

A parameterisation is also introduced which allows a second sowing, in case the first one fails (that is, after 2 weeks, the plant has not grown). This is to account for the fact that the first rains during the planting window might be isolated and not correspond to the real beginning of the rainy season: the sowing is then too early and the plant can not grow, because of water stress. This also mimics the behaviour of farmers who do re-sow in case nothing comes out after the first attempt (Graef and Haigis 2001).

Figure 6 compares the 1971–2000 mean sowing dates computed by ORCH-mil with the 1971–2000 mean sowing dates given by the regional centre Agrhymet, which we consider as a good approximation of ground truth (see Section 2.4). The two maps are fairly similar with sowing dates from early May in the south to end of July above 15°N. This zonal gradient is imposed by the northward progression of the monsoon system over the region. The larger area covered with late simulated sowing dates in ORCH-mil results from the extensive distribution of millet we have prescribed.

4.1.2 Simulated yields

Figure 6b shows the mean yield computed by ORCH-mil over 1971–2000, for the 90-day millet simulation. As expected, the spatial distribution of simulated yields is very close to the annual rainfall distribution (Fig. 5a), with a similar zonal gradient. The rainfall dependence induces a strong interannual variability of yields in the sahelian region where rainfall is more variable, as shown by the high values of the variation coefficient (standard deviation relative to the mean) in the north of the simulation domain (Fig. 6c).

Figure 6d shows attainable yields of 90-day millet as given by the regional centre Agrhymet (see Section 2.4). These observation-corrected values show a similar latitudinal pattern of mean yields: this general feature is correctly captured by ORCH-mil. However it also shows that ORCH-mil largely overestimates yield values, by a factor 2 to 5, an overestimation which increases towards low latitudes. Table 2 compares the observed (FAO) and simulated means and standard deviations of millet yield (from the same 90-day simulation) for Niger, Burkina-Faso, Chad, Senegal and Mali: ORCH-mil strongly overestimates both the mean and the inter-annual variability of yields.

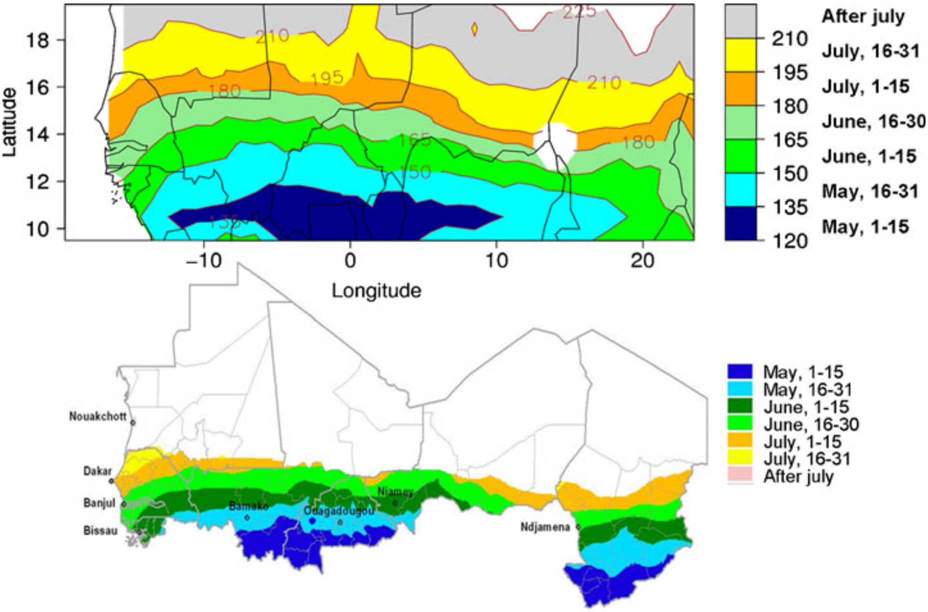

Fig. 5 Average sowing dates for millet (*top*), as computed by ORCH-mil over 1971–2000 (*bottom*), as given by the Agrhymet regional Centre over 1971–2000

This overestimation results from the differences between agricultural conditions in experimental research stations, and on-farm conditions. ORCH-mil, like SARRAH, reproduces the optimal growth conditions of an experimental station: an improved cultivar is grown, plants are not nutrient-limited, plant density is high, and crop management (against weeds, diseases and pests) is optimal. Thus, final

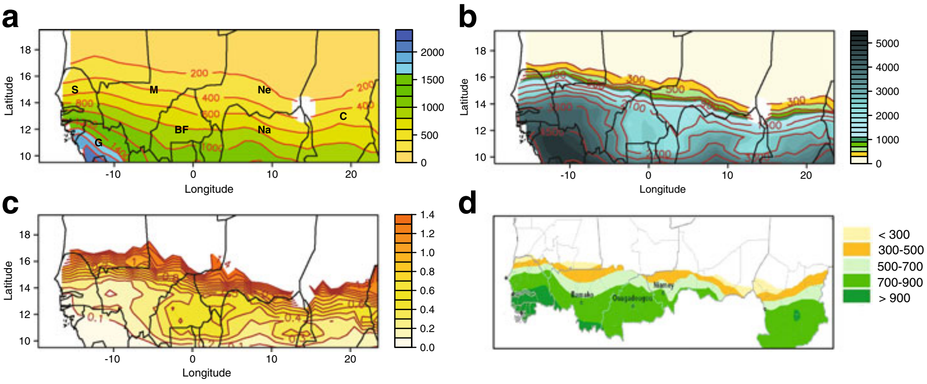

Fig. 6 **a** Mean annual rainfall (in mm) over 1965–2000, from the NCC data (*letters* indicate countries: *S* Senegal, *M* Mali, *Ne* Niger, *Na* Nigeria, *C* Chad, *G* Guinea, *BF* Burkina-Faso). **b** Average yield computed by ORCH-mil over 1971–2000, in kg/ha, for the 90-day variety. **c** Variation coefficient (standard deviation/mean) of simulated yields. **d** Average millet yields over 1971–2000, as given by Agrhymet, in kg/ha (*colours* correspond with **b**)

Table 2 Mean and standard deviation of nationally aggregated modelled yields and FAO yields (in tons of dry matter per hectare, tDM/ha)

	Mean		Standard deviation	
	FAO	ORCH-mil	FAO	ORCH-mil
Mali	0.67	2.81	0.12	0.35
Niger	0.36	1.38	0.06	0.57
Burkina-Faso	0.48	2.53	0.12	0.53
Senegal	0.51	3.1	0.11	0.38
Chad	0.45	2.46	0.08	0.41

yields can be considered as weather-dependant maximum attainable yields under rainfed conditions. As shown in Section 3.3, such yields reach 2–3 t/ha at the BNRS (around 100 gC/m^2); Murty et al. (2007) report similar values for millet and sorghum on experimental stations in India. Accordingly, ORCH-mil's simulated yields are of the same magnitude. However, many factors contribute to create a gap between such potential yields and actual on-farm yields: lack of fertilization and poor soil fertility, suboptimal management, pests, etc. Plants are also more sparsely sowed (given limitations on soil fertility, in particular), and instead of improved cultivars farmers most often grow local and traditional hardy varieties, which tend to be advantageously less sensitive to drought or climatic stress but yield a weaker production on average.

Because ORCH-mil does not account for all these yield-reducing factors, it unsurprisingly overestimates average observed yields. The fact that hardy cultivars are less sensitive to climate may also explain the overestimation of simulated yield interannual variability. Overestimating observed on-farm yields is a common shortfall in many crop modelling studies, for crop models are most often calibrated in controlled environments, not accounting for non-climatic factors. Other large-scale analysis in similar studies face similar issues: for groundnuts in India using the GLAM model, Challinor et al. (2004, 2005) define an empirical yield gap parameter to reduce simulated yields from climatic potential yields to average observed yields. In LPJ-ml, Bondeau et al. (2007) adjust the "maximum LAI" parameter to account for the different levels of crop management intensities across the world. In our case, some of the factors contributing to lower on-farm yields will in the future be accounted for in the frame of ORCHIDEE: lower plant densities can be simulated by prescribing higher bare soil fractions within the grid cell; the latest version of ORCHIDEE includes a representation of the nitrogen cycle and an explicit computation of nitrogen stresses (Zaehle and Friend 2010); finally, a new version of SARRAH is being calibrated for more traditional farmers' millet cultivars, and could be straightforwardly implemented into ORCH-mil.

In the present paper, the assumption we make is that this positive mean bias in crop production is relatively constant from year to year, and thus that the simulated (climate-driven) yield variability can still be compared to the observed variability.

4.2 Interannual variability of simulated and observed yields

In this section we focus on testing the ability of ORCH-mil to simulate the interannual variability of millet yields. This implies to assess how consistent the model is with the observed climate–yield relationship, and how it reproduces the observed yield interannual variability, not in absolute terms (as we showed in the previous section that it was overestimated in ORCH-mil) but in terms of standardized anomalies.

4.2.1 Correlations between climate and yields

In the context of rain-fed agriculture in semi-arid countries, cumulative rainfall can be expected to be the main driving climatic variable for crop production. Thus, in order to compare the first-order relationship between climate and yield in the observations and in the simulations, we compute the correlations over 1965–2000, at the national scale, between annual cumulative rainfall from the NCC dataset (which, as indicated in Section 2.3, is corrected by CRU values) and, respectively, observed and simulated yields. As indicated in Section 2.4, both yield (simulated and observed) and climate time series are detrended, as we are only interested here in interannual variability. The same analysis was carried out with other climatic variables (temperature, incident short-wave radiation) but did not give any significant results (not shown).

Table 3 shows the results for FAO yields. These correlations can be considered as a first-order "climate signal" in the observations. As expected, significant correlations appear: around 0.6 for Niger and Burkina-Faso, around 0.5 for Senegal and Chad (for 36-year time series, correlations above 0.33 are significant at the 5% level). Correlation for Mali surprisingly remains non significant (R = 0.26). However, as explained before (see Section 2.4), the accuracy of the FAO data must be considered carefully. In particular, the relationship between national yield and rainfall is not stationary for Mali and Senegal: correlations over 1965–1984 are respectively 0.58 and 0.6 (figures in brackets in Table 3), and fall to 0 for both countries over 1985–2000. Since there is no particular reason to believe that rainfall amounts from the CRU—which are used to correct the monthly rainfall amounts in the NCC dataset—became particularly wrong after 1984, nor that there was at that time in these countries a sudden increase in the irrigated fraction of staple crops—or other farming practices that can reduce the dependence of crop production on rainfall—this non-stationarity potentially highlights a discontinuity in census data from the FAO, rather than an actual change in the weather–yield relationship.

Correlations calculated from the ORCH-mil simulations of 90-day and 120-day millets (Table 4) are overall stronger than in reality, suggesting that the model overestimates the role of rainfall in crop production. In the simulations, rainfall is one of the few input variables to the model, whereas it is one of many in reality: other non-climatic factors also impact crop productivity, such as human management, soil fertility, biotic stresses, etc. Thus, an overestimation of the relationship between yield

Table 3 Correlations between FAO national yields and annual rainfall (from the NCC data, aggregated over each country)

Mali	0.34 (0.61)
Niger	0.64
Burkina-Faso	0.58
Senegal	0.49 (0.6)
Chad	0.49

Figures in brackets for Mali and Senegal indicate the correlation over 1965–1984

Table 4 Correlations between simulated yields and annual rainfall, aggregated over each country; first column is for the 90-day cycle simulation, second column for the 120-day cycle simulation

	90-day cycle	120-day cycle
Mali	0.63	0.73
Niger	0.81	0.72
Burkina-Faso	0.09	0.58
Senegal	0.72	0.64
Chad	0.86	0.56

and rainfall can be expected in the model, as has been noted in other modelling studies (for instance, Challinor et al. 2005).

The correlation between rainfall and simulated yield in Mali and Burkina Faso are stronger with the 120-day cultivar (respectively R = 0.73 and R = 0.58 for Mali and Burkina Faso) than with the 90-day cultivar. This can be explained by the southern extension of these two countries (compared to Senegal or Niger) that experience longer rainy seasons. These higher correlations suggest, as expected, that a longer cycle duration is more realistic in these countries, and that there is a need to differentiate millet varieties in West Africa in terms of cycle duration. In the following sub-section, we will consider for each country the most appropriate variety in our simulation (120-day for Mali and Burkina-Faso, 90-day for Niger, Mali, Chad and Senegal).

4.2.2 Correlations between simulated and observed yields

Correlations between observed and simulated yield are reported in Table 5: they are overall moderate. The highest correlation is obtained for Burkina-Faso and Niger (R = 0.53 and 0.47, respectively). Figure 7 shows that for these countries the model is, to a certain extent, able to reproduce some of the year-to-year variability of FAO yields. Table 3 suggest that this skill mainly results from these two countries showing the strongest climate signal in observations (R = 0.58 and 0.64, respectively). For Senegal, the correlation between observed and simulated yields significantly falls, as expected, from 0.49 over 1965–1984 to −0.03 for the rest of the period, which is consistent with the absence of climatic signal in the FAO yields after 1984. For Mali the correlation remains non-significant whatever the time period. This suggests a specific problem in the simulations over the Mali region. Finally, the correlation for Chad remains barely significant (R = 0.32), although this country seemed similar to Niger: millet cultivation areas are in dry northern latitudes (Fig. 4), and thus simulated yields show a strong rainfall dependency (R = 0.86, Table 4). Unlike Niger,

Table 5 Correlations between nationally aggregated modelled yields and FAO yields, over 1965–2000 (1965–1984)

Mali	0.15 (0.29)
Niger	**0.47**
Burkina-Faso	**0.53**
Senegal	0.29 (**0.48**)
Chad	0.32

Figures in brackets for Mali and Senegal indicate the correlation over 1965–1984. Figures in bold are significant at the 5% level

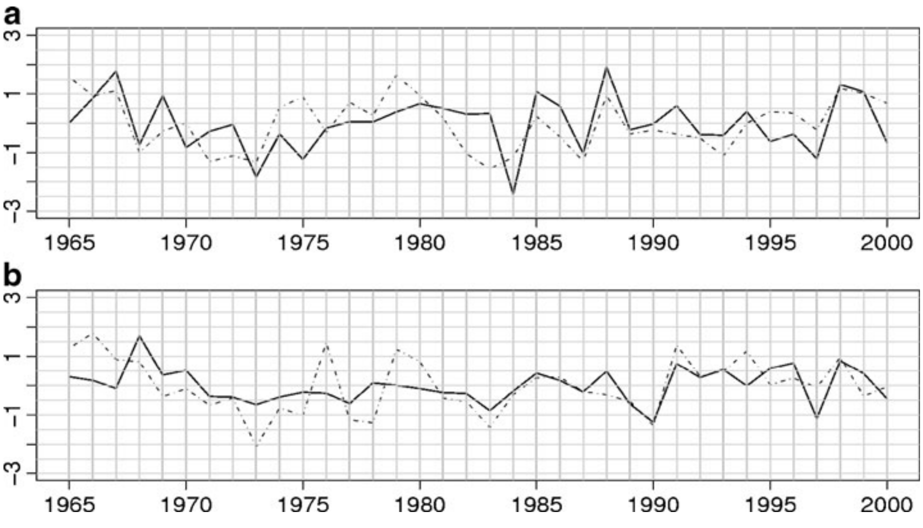

Fig. 7 Simulated (*dashed line*) and observed (*full line*) national yields for **a** Niger, **b** Burkina-Faso. **a** shows results for the 90-day crop cycle simulation, **b** results for the 120-day crop cycle simulation. Values are given in standardized anomalies: (x − mean(x))/std(x)

however, Chad shows a weak climate signal across the whole time period ($R = 0.49$, Table 3), so that simulated yields correlate poorly to observations.

Several general reasons can be pointed out to explain the modest model skill. First, any model is by nature imperfect: some processes might be inadequately represented, or even missing, in ORCH-mil, hampering its ability to capture the observed yield variability. Second, potential biases in the forcing data may also translate into biases in the simulation. In particular, if rainfall monthly amounts in the NCC dataset are corrected by the CRU data, the intraseasonal distribution ultimately relies only on the NCEP reanalysis, and thus can be questioned. Uncertainties also arise from the historical distribution of millet croplands: the assumption of a constant general pattern of millet areas over recent decades might be inappropriate. Finally, as previously mentioned in Section 2.4, we also underscore that observed yields are influenced by many non-climatic factors, whereas climate is the only driver of modelled yields: therefore, there is also an upper limit to the skill of any climate-only driven model at simulating national yields.

These limitations result in the correlations between observed and simulated yields remaining weaker than the correlations between observed yields and rainfall (Tables 3 and 5). Although this might suggest that cumulative rainfall is overall a better predictor of large-scale yields, one has to keep in mind that statistical relationships do not resolve biophysical processes, and therefore may not perform well under changing climates and changing environments. For example, climate/vegetation relationships do not account for the effects of future increased atmospheric CO_2 levels. Process-based modelling also allows accounting for the impacts of intraseasonal weather variability—provided it is well represented in the forcing data, and is significant enough to have a detectable impact on large-scale yield variability.

5 Modifications of surface properties and fluxes

In this section, we compare on a regional scale ORCH-mil with the standard version of ORCHIDEE in terms of land surface properties. Indeed, by including in ORCHIDEE a more realistic representation of croplands, we also modified some of the land surface biophysical properties (e.g. albedo, roughness length) and land–atmosphere fluxes: absorbed and emitted radiation, water and heat fluxes. Given that the seasonal cycle of phenology is improved in ORCH-mil, these variables can be expected to be more realistically simulated as well. Hence, we aim here at quantifying the differences we introduced in terms of surface energy budget, in order to get a first taste of how accounting explicitly for croplands in a biosphere model might feed back on the monsoon climatic system.

We run the same simulation as described in the previous section, but with the standard version of ORCHIDEE. As mentioned in the introduction, the C4 crop-PFT in this version is simulated as natural grassland with enhanced photosynthetic activity. This simulation is compared to the 90-day simulation by ORCH-mil presented in the previous section. In this section, because we are interested in the absolute differences between ORCH-mil and ORCHIDEE rather than in a comparison to observed data, we do not use the millet area map as in Section 4: we compare ORCH-mil and ORCHIDEE over the whole simulation domain.

Figure 8 shows the ratio, between ORCH-mil and ORCHIDEE, for the mean (over 1965–2000) annual net radiation, albedo, latent and sensible heat fluxes. One can see that, on average, net radiation (the energy available at the surface) is lower in ORCH-mil (Fig. 8a). This means that less energy will be returned to the atmosphere in the form of latent and sensible heat. This is consistent with the higher albedo in ORCH-mil (Fig. 8b); however, one can see that if the mean annual latent heat flux is indeed reduced (Fig. 8c) (in some regions by more than 25%), in the mean time the sensible heat flux slightly increases (Fig. 8d) and the sum of those changes exceeds the change in absorbed solar radiation. Hence, it is not possible

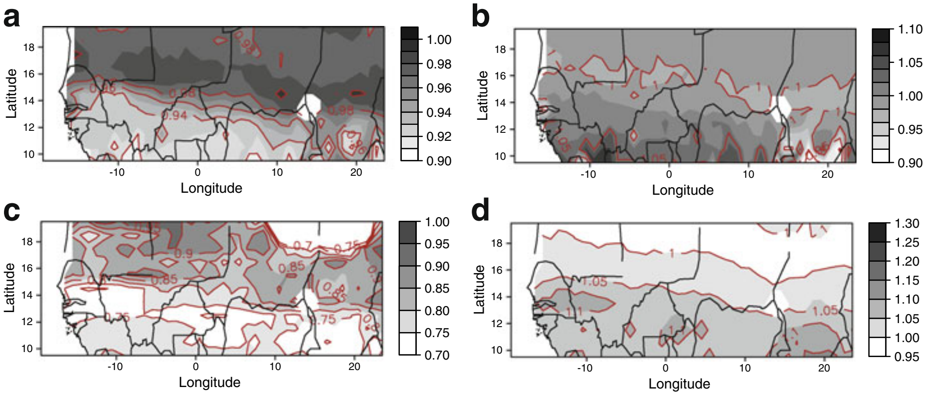

Fig. 8 Ratio between ORCH-mil and ORCHIDEE for 36-year average of annual value of **a** net radiation, **b** albedo, **c** latent heat flux, **d** sensible heat flux

to attribute this reduction in net radiation solely to the higher albedo in the crop simulation.

To further analyse these differences, the mean seasonal cycle of those same variables are illustrated on Fig. 9, averaged over the 36 years of simulation and for a small regional window (2°W:7°E–12:14°N) corresponding to a domain with large differences in latent heat flux (Fig. 8c). One can see that the plant cycle is on average shorter in ORCH-mil (upper-left graph, LAI in dots): as discussed in Section 3, this is because ORCHIDEE simulates croplands as natural grasslands that gradually decline throughout fall and winter, whereas in ORCH-mil the phenological cycle is shorter and abruptly ends with a harvest at the end of the rainy season (since several years and pixels are averaged, the abrupt harvest is here averaged to a more gradual decline). It also shows that the average maximum LAI is reduced in ORCH-mil, from 4 in ORCHIDEE to a more realistic value of 2.

Because of the shorter vegetation cycle, evapotranspiration (latent heat flux) at the end of the growing season is, on average, reduced (same graph, solid lines). For the same reason, albedo (Fig. 9c) increases in ORCH-mil at the end of the year (the last 120 days): while in standard ORCHIDEE the senescence of grass's leaves is very slow, thus keeping bare soil shaded by vegetation, in ORCH-mil harvested cropland turns directly to bare soil, the albedo of which is larger than grass in this region. This higher albedo results in a lower net radiation (Fig. 9d) and thus the increase in sensible heat flux (Fig. 9b) only partially offsets, on average, the decrease in latent heat flux resulting from the plant being harvested. This increase in sensible heat flux, however, implies a higher soil temperature, up to 4 K hotter (Fig. 9f).

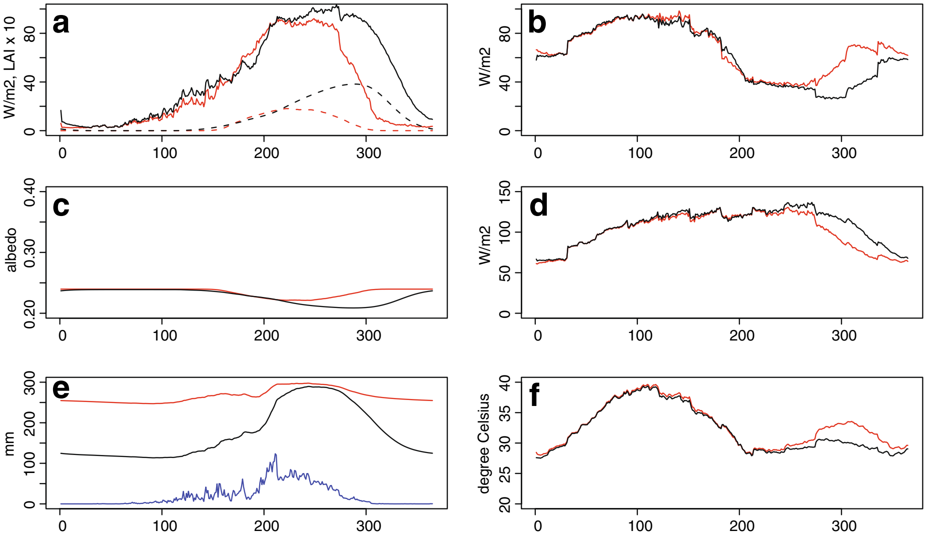

Fig. 9 Mean annual cycle, over the 36 years of simulation and a 2°W–7°E / 12°–14°N window, for ORCH-mil (*red*) and ORCHIDEE (*black*), for **a** latent heat flux (*full lines*) and LAI, scaled up by a factor 10 (*dashed lines*), **b** sensible heat flux, **c** albedo, **d** net radiation, **e** total soil water content, and rainfall (*blue line*) scaled up a factor 10, **f** soil temperature

The shortening of the vegetation's cycle also causes some modifications in the soil water budget: as less water is evaporated at the end of the rainy season (since the crop is harvested), more water remains in the soil and is available during the dry season of the following year. Thus, on average total soil water content along the year is increased in ORCH-mil compared to standard ORCHIDEE (Fig. 9e). While this effect may be qualitatively realistic, its magnitude in the model is certainly questionable.

In summary, the differences in surface energy budget between ORCH-mil and ORCHIDEE mainly result from the differences in cycle duration (as shown on Fig. 9). This explains the latitudinal gradient of changes that appears on Fig. 8: these differences in cycle length between natural grasses and fixed-duration millet widen with decreasing latitudes. As we only considered the 90-day simulation of ORCH-mil, in which crop cycle length is too short in the south of the simulation domain (see previous section), one may expect these differences in energy budget at low latitudes to be overestimated. However, the same plots with the 120-day variety produce a similar general pattern with only slightly lower differences: for instance a maximum latent heat flux reduction of 20 % instead of 25% (not shown).

If we try to extrapolate from our off-line (decoupled from an atmospheric general circulation model) results and put them in the context of the dynamics of the monsoon system, we can hardly expect any change regarding the onset of the monsoon rains. Indeed, under a tropical monsoon climate, with only one short rainy season and thus one growing season for vegetation, the phenology of croplands and natural grasslands does not differ much. In the region considered here, natural vegetation growth starts as soon as the rainy season begins, and farmers generally try to sow as early as possible: thus, the beginning of the seasonal cycle of natural and cultivated vegetation tends to be synchronous. The largest differences will be obtained at the end of the rainy season, when crops are harvested, unlike grasslands that continue to cover the ground. As a consequence, accounting explicitly for croplands across West Africa in a coupled biosphere/atmosphere model would probably influence the retreat of the monsoon rains rather than their initiation. But this deserves further investigation since the question of the interannual memory of the monsoon system via land surface mechanisms—that is, the influence of conditions at the end of season 'n' on the conditions at the beginning of season 'n + 1'—remains open (Philippon and Fontaine 2002; Douville et al. 2006; Fontaine et al. 2007). The largest amount of soil moisture that remains in the soil when crops are planted instead of super-grassland could very well influence the energy budget at the start of the following monsoon season.

Naturally, these modifications here result from an idealized experiment where a 100% grassland land-cover is replaced by a 100% cropland land-cover. These modifications have to be weighted by the crop land-cover fraction: Fig. 4 indicates that this will on average significantly scale down the impacts over the whole region. However, it also shows that crops can locally represent a dominant part of the landscape (the maximum millet fraction on a 5' × 5' pixel is 67.5%). Since meso-scale seasonal variability in surface fluxes and soil moisture has the potential to feed back on atmospheric circulations and rainfall (Taylor et al. 2007; Taylor 2008), the differences between grasslands and croplands we highlighted may have local impacts on atmospheric conditions. Moreover, present-day land-use intensity is likely to increase in coming decades, as the expected increase in population will inevitably require expanding cultivated areas, in addition to increasing yield (according to Griffon 2006 (p.153), food production in Africa will have to quintuple between 2000 and 2050). Thus, more realistically accounting for croplands across West Africa may be an essential step to study the future of the West African Monsoon in a coupled biosphere/atmosphere model.

6 Conclusion and outlooks

It has been suggested that a relevant framework to address the twofold issue of crops–climate interactions (the effect of climate on crops as well as the feedback of croplands on climate) may be the extension of global vegetation models, coupled to climate models, in order to include a better representation of croplands. Here, by introducing into the land surface model ORCHIDEE processes and parameterisations taken from an existing crop model calibrated over West Africa, we develop an original model for tropical crops, which is a first step towards such an integrated crop-climate model.

In terms of crop and yield simulation, it realistically simulates growth and development of millet on an experimental station in Senegal. When applied over West Africa, the spatial distribution of simulated sowing dates and yields is realistic. However, when assessed against national FAO data, yields mean values and variability are largely overestimated. This mainly results from running a single highly-productive, nutrient-unlimited and intensely-managed crop-type parameterisation across the whole simulation domain. The model shows a spatio-temporal dependence of millet yields on rainfall that is broadly consistent with observations. The model, as expected, somehow overestimates the large-scale climate signal (defined as the correlation at national scale between rainfall and yields): across several countries, correlations range from 0.39 to 0.64 in observations and from 0.58 to 0.86 in simulations. The model skill, e.g. its ability to reproduce the observed time series of yield anomalies, remains moderate: the best correlations are 0.53 for Burkina-Faso, 0.47 for Niger. Since simulated yields are highly rainfall-dependent, both spatially and temporally, the model skill is generally greater where the climate signal in the observations is stronger. Accounting for different millet varieties in terms of cycle duration substantially improved our results in certain countries.

In terms of land surface properties, we compared ORCH-mil with the standard version of ORCHIDEE, which represents croplands as natural grasslands. The main difference resulting from an improved representation of croplands is the shorter plant cycle, because croplands are harvested and replaced by bare soil. Thus, explicitly accounting for croplands results, on average, in modifications of the surface energy budget during the second half of the rainy season: evapotranspiration is reduced (by as much as 25% locally across part of the sahelian domain), sensible heat flux increases. Since albedo increases as well, net radiation is reduced, meaning that less energy is in the end returned to the atmosphere. In terms of water budget, the reduced evaporation also leads to higher water content in the soil at the end of the crop growing season. The effects on the atmosphere of such modifications of the surface budgets (water, energy) should be investigated by coupling ORCH-mil to an AGCM.

The development of ORCH-mil and the results shown in this paper are a first step to study crops–climate interactions. Further work is needed to improve the accuracy of the model, in particular in terms of yield simulation.

First, it would be necessary to test ORCH-mil on other locations where in situ measurements are available, in order to better assess the robustness of the model, and its ability to capture the impacts of climate variability. In order to reduce the average gap between observed and simulated average yields, the model should account for the differences between the intensive growth conditions it simulates and the more extensive on-farm growth conditions. This could be done empirically by modifying some parameters in the model as a proxy to different level of crop management intensity, or by *a posteriori* calibrating a large-scale "yield gap" parameter. A more satisfying approach would be to explicitly model some of these yield-reducing factors, for example the effect of insufficient fertilization by using the new ORCHIDEE-CN version which includes the N cycle.

Simulations at the regional scale, then, need to more consistently account for the spatial heterogeneity in crop varieties, particularly in terms of crop duration, as highlighted in this study: for example through a parameterisation of the crop cycle length as a function of the sowing date.

Overall, including croplands in a DGVM may offer a consistent framework for integrated crop–climate interactions studies. However, in our case the exact extent to which such a model can be used as an efficient large-scale predictor for crop production still needs to be demonstrated: multiple uncertainties arise from the mismatch between the simplicity of a single large-scale model simulation and the complexity and diversity of local agronomical situations. On the other hand, such a model is interesting to analyse the large-scale feedbacks of crops to climate: biophysical effects, like changes in water and momentum fluxes, or biogeochemical effects, like modifications in the vegetation carbon budget. In the case of West Africa, this could contribute to analyze the potential impacts of agricultural land-use on land–atmosphere interactions, and on the West African Monsoon system. Further development is naturally needed in order to extend this modelling approach to other regions of the world, and other crops.

Acknowledgements We would like to gratefully acknowledge Christian Baron and the Ecotrop Team at CIRAD (French Agricultural Research Centre for Agricultural Development) for providing us with the SARRAH model and with the Bambey experimental station data, as well as for their useful advice and comments on the work presented here. We also gratefully thank Seydou Traoré and the Agrhymet Centre in Niamey for providing us with maps of millet sowing dates and yields. We thank the three anonymous reviewers for their useful comments and suggestions. Alexis Berg is supported by the Region Ile-de-France PhD-funding program.

References

Affholder F (1997) Empirically modelling the interaction between intensification and climatic risk in semiarid regions. Field Crops Res 52:79–93

Ati OF, Stigter CJ, Oladipo EO (2002) A comparison of methods to determine the onset of the growing season in northern Nigeria. Int J Climatol 22:731–742

Baron C, Reyniers FN, Clopes A, Forest F (1999) Applications du logiciel SARRA à l'étude de risques climatiques. Agriculture et Développement 24:89–97

Baron C, Sultan B, Balme M et al (2005) From GCM grid cell to agricultural plot:scale issues affecting modelling of climate impact. Phil Trans R Soc B: Biol Sci 360:2095–2108

Betts R (2005) Integrated approaches to climate-crop modelling: needs and challenges. Phil Trans R Soc B: Biol Sci 360:2049–2065

Bondeau A, Smith PC, Zaehle S et al (2007) Modelling the role of agriculture for the 20th century carbon balance. Glob Chang Biol 13:679–706

Boucher O, Myhre G, Myhre A (2004) Direct human influence of irrigation on atmospheric water vapour and climate. Clim Dyn 22:597–603

Brisson N, Gary C, Justes E et al (2003) An overview of the crop model STICS. Eur J Agron 18: 309–332

Challinor AJ, Slingo JM, Wheeler TR et al (2003) Toward a combined seasonal weather and crop productivity forecasting system: determination of the working spatial scale. J Appl Meteorol 42:175–192

Challinor AJ, Wheeler T, Craufurd PQ et al (2004) Design and optimisation of a large-area process-based model for annual crops. Agric For Meteorol 124:99–120

Challinor AJ, Wheeler T, Craufurd PQ et al (2005) Simulation of crop yields using ERA-40: limits to skill and nonstationarity in weather–yield relationships. J Appl Meteorol 44:516–531

Ciais P, Reischstein M, Viovy N, Granier A, Ogée J et al (2005) Europe-wide reduction in primary productivity caused by the heat and drought in 2003. Nature 437(7058):529–533

Collatz GJ, Ribas-Carbo M, Berry JA (1992) Coupled photosynthesis-stomatal conductance model for leaves of C4 plants. Aust J Plant Physiol 19:519–538

de Noblet-Ducoudré N, Gervois S, Ciais P et al (2004) Coupling the soil–vegetation–atmosphere–transfer scheme ORCHIDEE to the agronomy model STICS to study the influence of croplands on the European carbon and water budgets. Agronomie 24:1–11

de Rosnay P, Polcher J (1998) Modelling root water uptake in a complex land surface scheme coupled to a GCM. Hydrol Earth Syst Sci 2:239–256

de Rosnay P, Polcher J, Laval K, Sabre M (2003) Integrated parameterization of irrigation in the land surface model ORCHIDEE. Validation over Indian Peninsula. Geophys Res Lett 30(19). doi:10.1029/2003GL018024

de Rosnay P, Drusch M, Boone A, Balsamo G, Decharme B, Harris P, Kerr Y, Pellarin T, Polcher J, Wigneron J-P (2009) The AMMA Land Surface Model Intercomparison Experiment coupled to the Community Microwave Emission Model: ALMIP-MEM. J Geophys Res 114. doi:10.1029/2008JD010724

Dingkuhn M, Baron C, Bonnal V, Maraux F, Sarr B, Sultan B, Clopes A, Forest F (2003) Decision-support tools for rain-fed crops in the Sahel at the plot and regional scale. In: Struif-Bontkes TE, Wopereis MCS (eds) A practical guide to decision-support tools for agricultural productivity and soil fertility enhancement in Sub-Saharan Africa. IFDC, CTA, pp 127–139

Donner SD, Kucharik CJ (2003) Evaluating the impacts of land management and climate variability on crop production and nitrate export across the upper Mississippi Basin. Glob Biogeochem Cycles 17:1085

Douville H, Conil S, Tyteca S, Voldoire A (2006) Soil moisture memory and West African monsoon predictability: artefact or reality? Clim Dyn 28:723–742

Ducoudré N, Laval K, Perrier A (1993) SECHIBA, a new set of parameterisations of the hydrologic exchanges at the land–atmosphere interfaces within the LMD atmospheric general circulation model. J Clim 6:248–273

Dyson T (2001) World food trends: a Neo-Malthusian prospect? Proc Am Philos Soc 145(4): 438–455

Feddema JJ, Oleson KW, Bonan GB et al (2005) A comparison of a GCM response to historical anthropogenic land cover change and model sensitivity to uncertainty in present-day land-cover representations. Clim Dyn 25:581–609

Foley JA, Prentice IC, Ramankutty N et al (1996) An integrated biosphere model of land surface processes, terrestrial carbon balance, and vegetation dynamics. Glob Biogeochem Cycles 10: 603–628

Foley JA, Coe MT, Scheffer M et al (2003) Regime shifts in the Sahara and Sahel: interactions between ecological and climatic systems in Northern Africa. Ecosystems 6:524–532

Foley JA, DeFries RS, Asner GP et al (2005) Global consequences of land use. Science 309:570–574

Fontaine B, Louvet S, Roucou P (2007) Fluctuations in annual cycles and inter-seasonal memory in West Africa: rainfall, soil moisture and heat fluxes. Theor Appl Climatol 88:57–70

Gervois S, de Noblet-Ducoudré N, Viovy N et al (2004) Including croplands in a global biosphere model: methodology and evaluation at specific sites. Earth Interact 8:1–25

Giannini A, Saravanan R, Chang P (2003) Oceanic forcing of Sahel rainfall on interannual to interdecadal time scales. Science 302:1027–1030

Graef F, Haigis J (2001) Spatial and temporal rainfall variability in the Sahel and effects on farmers' management strategies. J Arid Environ 48/2:221–231

Griffon M (2006) Nourrir la planète. Ed. Odile Jacob, Paris

Hansen JW (2002) Realizing the potential benefits of climate prediction to agriculture: issues, approaches, challenges. Agric Syst 74:309–330

Krinner G, Viovy N, de Noblet-Ducoudré N et al (2005) A dynamic global vegetation model for studies of the coupled atmosphere–biosphere system. Glob Biogeochem Cycles 19:GB1015. doi:10.1029/2003GB002199

Kucharik CJ, Brye KR (2003) Integrated biosphere simulator (IBIS) yield and nitrate loss predictions for Wisconsin maize receiving varied amounts of nitrogen fertilizer. J Environ Qual 32: 247–268

Monfreda C, Ramankutty N, Foley JA (2008) Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Glob Biogeochem Cycles 22:GB1022. doi:10.1029/2007GB002947

Murty MVR, Piara Singh, Wani SP, Khairwal IS, Srinivas K (2007) Yield gap analysis of Sorghum and Pearl Millet in India using simulation modelling. Global theme on agroecosystems report no. 37. Patancheru 502 324, International Crops Research Institute for the Semi-Arid Tropics, Andhra Pradesh, India, 82 pp

New M, Hulme M, Jones P (1999) Representing twentieth-century space–time climate variability. Part I: development of a 1961–90 mean monthly terrestrial climatology. J Climate 12:829–856

New M, Hulme M, Jones P (2000) Representing twentieth-century space–time climate variability. Part II: development of 1901–96 monthly grids of terrestrial surface climate. J Climate 13:2217–2238

Ngo-duc T, Polcher J, Laval K (2005) A 53-year forcing data set for land surface models. J Geophys Res 110:DO6116. doi:10.1029/2004JD005434

Ogallo LA, Boulahya MS, Keane T (2000) Applications of seasonal to interannual climate prediction in agricultural planning and operations. Agric For Meteorol 103:159–166

Oram PA (1989) Sensitivity of agricultural production to climatic change, an update. In: Climate and food security. IRRI, Manila, Philippines, pp 25–44

Osborne T, Lawrence D, Challinor AJ et al (2007) Development and assessment of a coupled crop-climate model. Global Chang Biol 13:169–183

Penning de Vries FWT, Jansen DM, ten Berge HFM, Bakema A (1989) Simulation of ecophysiological processes of growth in several annual crops. PUDOC, Wageningen, The Netherlands, pp 291

Philippon N, Fontaine B (2002) The relationship between the Sahelian and previous 2nd Guinean rainy seasons: a monsoon regulation by soil wetness? Ann Geophys 20:575–582

Pielke RA Sr, Adegoke JO, Chase TN et al (2007) A new paradigm for assessing the role of agriculture in the climate system and in climate change. Agric For Meteorol 142:234–254

Ramankutty N (2004) Croplands in West Africa: a geographically explicit dataset for use in models. Earth Interact, 8-023

Ramankutty N, Evan AT, Monfreda C, Foley JA (2008) Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. Glob Biogeochem Cycles 22:GB1003. doi:10.1029/2007GB002952

Ruimy A, Dedieu G, Saugier B (1996) TURC: a diagnostic model of continental gross primary productivity and net primary productivity. Glob Biogeochem Cycles 10:269–285

Samba A (1998) Les logiciels Dhc de diagnostic hydrique des cultures: prévision des rendements de mil en zones soudano-sahéliennes de l'Afrique de l'Ouest. Sécheresse 9:281–288

Samba A, Sarr B, Baron C, Gozé E, Maraux F, Clerget B, Dingkuhn M (2001) La prévision agricole à l'échelle du Sahel. In: Malézieux E, Trébuil G, Jaeger M (eds) Modélisation des agro-écosystème et aide à la décision. CIRAD and INRA, Montpellier, pp 243–262

Scholze M, Bondeau A, Ewert F, Kucharik C, Priess J, Smith P (2005) Advances in large-scale crop modelling. Eos Trans AGU 86:245–247

Sinclair TR, Mudchow RC (1999) Radiation use efficiency. Adv Agron 65:215–265

Sitch S, Smith B, Prentice IC et al (2003) Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model. Glob Chang Biol 9: 161–185

Smith PC, de Noblet-Ducoudré N, Ciais P, Peylin P, Viovy N, Meurdesoif Y, Bondeau A (2010) European-wide simulations of croplands using an improved terrestrial biosphere model: phenology and productivity. J Geophys Res 115:G01014. doi:10.1029/2008JG000800

Sultan B, Baron C, Dingkuhn M et al (2005) Agricultural impacts of large-scale variability of the West African Monsoon. Agric For Meteorol 128:93–110

Taylor CM (2008) Intraseasonal land–atmosphere coupling in the West African Monsoon. J Climate 21:636–6648

Taylor CM, Parker DJ, Harris P (2007) An observational case study of mesoscale atmospheric circulations induced by soil moisture. Geophys Res Lett 618(34):L15801

Wang G, Elathir EA (2000) Role of vegetation dynamics in enhancing the low-frequency variability of the Sahel rainfall. Water Resour Res 36:1013–1022

Wang G, Elathir EA, Foley JA, Pollard D, Levis S (2004) Decadal variability of rainfall in the Sahel: results from the coupled GENESIS–IBIS atmosphere–biosphere model. Clim Dyn 22:625–637

Zaehle S, Friend AD (2010) Carbon and nitrogen cycle dynamics in the O-CN land surface model: 1. Model description, site-scale evaluation, and sensitivity to parameter estimates. Glob Biogeochem Cycles 24:GB1005. doi:10.1029/2009GB003521

Zheng X, Eltahir EA (1997) The response to deforestation and desertification in a model of West African monsoons. Geophys Res Lett 24(2):155–158

Zheng X, Eltahir EA (1998) The role of vegetation in the dynamics of the West African Monsoons. J Climate 11:2078–2096