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Climate change impact and potential adaptation strategies under alternate climate scenarios for yam production in the sub-humid savannah zone of West Africa

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Abstract Globally, yam (*Dioscorea* spp.) is the fifth most important root crop after sweet potatoes (*Ipomoea batatas* L.) and the second most important crop in Africa in terms of production after cassava (*Manihot esculenta* L.) and has long been vital to food security in sub-Saharan Africa (SSA). Climate change is expected to have its most severe impact on crops in food insecure regions, yet very little is known about impact of climate change on yam productivity. Therefore, we try estimating the effect of climate change on the yam (variety: Florido) yield and evaluating different adaptation strategies to mitigate its effect. Three regional climate models REgional MOdel (REMO), Swedish Meteorological and Hydrological Institute Regional Climate Model (SMHIRCA), and Hadley Regional Model (HADRM3P) were coupled to a crop growth simulation model namely Environmental Policy Integrated Climate (EPIC) version 3060 to simulate current and future yam yields in the Upper Ouémé basin (Benin Republic). For the future, substantial yield decreases were estimated varying according to the climate scenario. We explored the advantages of specific adaptation strategies suggesting that changing sowing date may be ineffective in counteracting adverse climatic effects. Late maturing cultivars could be effective in offsetting the adverse impacts. Whereas, by coupling irrigation and fertilizer application with late maturing cultivars, highest increase in the yam productivity could be realized which accounted up to 49 % depending upon the projection of the scenarios analyzed.

Keywords Adaptation · Africa · Climate change · EPIC model · Tuber crops · Yield

1 Introduction

Climate change is very likely to have an overall negative effect on yields of major cereal crops across Africa, with strong regional variability in the degree of yield reduction (Niang et al. 2014; Berg et al. 2013). Africa's food production systems are among the world's most vulnerable because of extensive reliance on rain-fed crop production, high intra- and inter-seasonal climate variability, recurrent droughts and floods that affect both crops and livestock,

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and persistent poverty that limits the capacity to adapt. Several recent studies since the United Nations Intergovernmental Panel on Climate Change Fourth Assessment Report (IPCC AR4) indicate that climate change will have variable impacts on non-cereal crops, with both production losses and gains possible (low confidence) (Niang et al. 2014). For climate change impact assessment, crop growth models have been widely used to evaluate crop responses (development, growth, and yield) by combining future climate conditions, obtained from global circulation models (GCMs) or regional circulation models (RCMs) with the simulation of carbon dioxide (CO_2) physiological effects derived from crop experiments (Moriondo et al. 2011). Research in developing countries indicate that climate change impacts on agriculture can be reduced through human adaptations such as adjusting sowing dates, changing cropping patterns (Tingem et al. 2008), or adopting higher yielding varieties (Njie et al. 2006). This is of importance for tuber crops and in particular for yam in Benin Republic as tuber crops constitute the major staple crop for many subsistence farms in the humid and sub-humid tropics (Srivastava et al. 2012). Yam (*Dioscorea* spp.) is the third most important tropical root crop after cassava (*Manihot esculenta* L.) and sweet potato (*Ipomoea batatas* L.) in West Africa, Central America, the Caribbean, Pacific Islands, and Southeast Asia. Yam is a multispecies crop, and the most predominant species is water yam (*Dioscorea alata* L.). Yams are distributed throughout the sub-tropics and tropics; however, about 91 % of the world's production is in West Africa (FAO 2014). In the yam belt of West Africa, the crop contributes more than 200 dietary calories per person each day for over 60 million people (Lawal et al. 2012), generates income from local and international trade, and constitutes an integral part of sociocultural life (Adejumo et al. 2013; Asiedu and Sartie 2010). Yam possesses excellent storage properties. It can be stored for 4 to 6 months without refrigeration and provides an important food safety net between growing seasons. Roots and tubers of these crops provide a cheap source of energy and vital nutrients to many people. Therefore, these crops are a main resource for food security, employment, and income in developing countries (Raymundo et al. 2014).

The ability to meet the future yam demands may hinge upon proper assessment of medium- and long-term yam production vulnerability to climate change and the measures taken to adapt accordingly. Therefore, the objective of this study was to assess the impact of climate change on yam production as one of the major global tuber crops and to evaluate a set of adaptation strategies namely changes in the sowing date, adoption of improved crop cultivars, use of irrigation water, and fertilizer application to alleviate the effect of climate change on yam production in the sub-humid tropical savannah zone of West Africa.

2 Methods

The approach adopted in this study was to assess the climate change impact on yam variety: Florido, introduced by Institut de Recherches Agronomiques Tropicales (IRAT) production as well as possible adaptation strategies to cope with its detrimental effect in the Upper Ouémé basin (a typical catchment within the sub-humid savanna zone of West Africa) by combining regional climate model outputs, a regional soil database, and regional cropland database with the Environmental Policy Integrated Climate (EPIC) crop growth simulation model. Comparison of EPIC output for baseline (1961–2000) and time horizon (2011–2050) provides an idea and insight into how yam yields may change under the IPCC Special Report on Emissions Scenarios (SRES)—A1B and B1 scenarios. The SRES A1B and B1 have been chosen as the primary scenarios to investigate since they portray a good range of possibilities between a pessimistic and optimistic projection.

We used the EPIC crop growth model. It is one of the most widely used crop models for studies on climate change impacts in the agricultural sector (White et al. 2011). It has been used for assessments of crop production (Balkovič et al. 2013), climate change (Liu et al. 2013; Niu et al. 2009; Tan and Shibasaki 2003), water resource use (Liu and Yang 2010) as well as carbon sequestration, greenhouse gas (GHG) mitigation, and biofuel studies (Izaurralde et al. 2012), and recent studies using EPIC to estimate small holder and commercial crop yields in West Africa (Srivastava et al. 2012; Gaiser et al. 2010) and all SSA (Folberth et al. 2012) showed a good reproduction of reported yields. The good performance of the model in the previous studies renders EPIC highly suitable for the purpose of the present study.

2.1 Study region and simulation units

The Upper Ouémé basin covers an area of 14,500 km^2 within the Republic of Bénin. The climate is tropical sub-humid with a mean annual temperature of 26.8 °C and mean annual precipitation of 1,150 mm (Mulindabigwi et al. 2008). The climate and soil conditions in the basin are typical for the large savanna systems of the sub-humid tropics which span from South America to Africa and Asia and which are dominated in Africa by tuber-cereal mixed cropping systems (Hall et al. 2001).

The catchment has been sub-divided into 121 sub-basins. Each sub-basin is composed of up to 15 hydrological and more than 30 agronomic response units of variable size which constitute the spatial simulation units land use soil association climate units (LUSAC). A total of 7,200 simulation units were identified. The LUSAC units have variable surface and represent an area with similar climate conditions, soil characteristics, and a representative crop and soil management. All data were gathered in the database of the spatial decision support system Protection du sol Et Durabilité des Ressources agricoles dans le bassin versant de l'Ouémé (PEDRO) (Enders et al. 2010; Gaiser et al. 2010), which combines the agro-ecosystem model EPIC with the hydrological model Soil Water Assessment Tool (SWAT) (Arnold et al. 1998). PEDRO provided representative soil profile data for the dominant soil type of each of the 38 mapping units of the soil association map (Table 1). Topographical information for each sub-basin including average slope inclination and length were extracted from the digital elevation model (DEM) provided by the global Satellite Radar Topographic Mission (SRTM).

Tuber yield of yam was calculated within each LUSAC for the period of 40 years (1961–2000) and 50 years (2011–2050). Then, tuber yields were aggregated from the LUSAC level to the basin level according to the procedure described by Gaiser et al. (2009) (Fig. 1) taking into account the area share of the LUSAC within the basin in order to obtain the average grain yield Y_s as

$$Y_s = \sum_i^N Y_i * Area_i$$

where Y_s is the average tuber yield over the basin in Mg ha^{-1} a^{-1}, Y_i is the tuber yield in LUSAC unit i in Mg ha^{-1} a^{-1}, and Area$_i$ is the decimal area percentage of LUSAC unit i in the basin.

2.2 EPIC model

EPIC is a biophysical model that can simulate crop biomass production, soil evolution, and their mutual interactions given detailed farm management practices and climate data (Williams 1995). EPIC calculates daily potential biomass as a function of solar radiation, leaf area index

Table 1 Representative soil profile data for the dominant soil type of each of the 38 mapping units of the soil association map

Mapping units	Soil depth (cm)	Org. Carbon (g/kg)	pH H2O	Texture class	Drainage	WRB[a]	French soil classification
1	53	12.4	4.9	Loamy Sand	Moderate	Regosol	Sols peu evolué quarzite
2	58	8.0	4.9	Sand	Moderate	Regosol	Sols mineraux bruts
3	65	7.8	5.2	Loamy Sand	well	Ferralsol	Sols ferralitiques
4	101	5.0	4.8	Loamy Sand	imperfectly	Lixisol	Sols ferugineux lessivé induré
5	104	7.2	5.9	Loamy Sand	imperfectly	Gleysol	Sol hydromorphique
6	104	8.2	5.5	Loamy Sand	well	Cambisol	Sol brun eutrophe hydromorphe
7	106	6.7	5.8	Sandy Loam	well	Luvisol	Sol ferrugineux peu lessivé
8	117	3.8	5.0	Loamy Sand	well	Lixisol	Sol ferrugineux lessivé
9	119	3.6	5.3	Loamy Sand	well	Lixisol	Sol ferrugineux lessivé induré
10	130	5.4	5.8	Sandy Loam	Moderate	Luvisol	Sol ferrugineux peu lessivé
11	136	1.4	5.1	Loamy Sand	well	Lixisol	Sol ferrugineux lessivé
12	136	5.6	5.1	Sandy Loam	Moderate	Lixisol	Sol ferrugineux lessivé induré
13	143	2.8	4.9	Loamy Sand	Moderate	Ferralsol	Sols ferralitiques faiblement désaturé
14	143	5.5	5.9	Loamy Sand	Moderate	Ferralsol	Sols ferralitiques rajeunis
15	149	11.5	5.2	Sandy Loam	Moderate	Lixisol	Solferrugineux lessivé sans concretions
16	156	4.7	5.8	Loamy Sand	Moderate	Lixisol	Sol ferrugineux lessivé avec concretions
17	156	3.8	5.8	Loamy Sand	well	Lixisol	Sol ferrugineux lessivé
18	156	3.9	5.7	Loamy Sand	well	Lixisol	Sol ferrugineux lessivé
19	156	8.0	5.7	Loamy Sand	Moderate	Lixisol	Sol ferrugineux lessivé
20	156	2.1	5.9	Loamy Sand	well	Acrisol	Sol ferrugineux appauvris sans concretions
21	156	5.5	5.2	Sandy Loam	well	Ferralsol	Sols ferralitiques
22	162	3.2	5.0	Sandy Loam	well	Ferralsol	Sols ferralitiques
23	169	3.2	5.1	Loamy Sand	well	Lixisol	Sol ferrugineux lessivé sans concretions
24	169	5.4	5.8	Sandy Loam	imperfectly	Lixisol Sol	ferrugineux lessivé induré
25	182	4.6	5.8	Sandy Loam	well	Lixisol	Sol ferrugineux lessivé avec concretions
26	182	4.6	5.8	Sandy Loam	well	Lixisol	Sol ferrugineux lessivé avec concretions
27	183	5.1	6.1	Clay Loam	imperfectly	Luvisol	Sol ferrugineux peu lessivé
28	188	6.1	6.2	Silty Clay	poorly	Luvisol	Sol ferrugineux peu lessivé
29	195	8.8	6.4	Silty Clay	imperfectly	Luvisol	Sol ferrugineux peu lessivé
30	195	6.5	5.8	Loamy Sand	well	Luvisol	

Table 1 (continued)

Mapping units	Soil depth (cm)	Org. Carbon (g/kg)	pH H2O	Texture class	Drainage	WRB[a]	French soil classification
							Sol ferrugineux peu lessivé
31	195	6.5	5.9	Sand	well	Luvisol	Sol ferrugineux peu lessivé
32	195	6.4	6.1	Sandy Loam	imperfectly	Luvisol	Sol ferrugineux hydromorphiques
33	195	3.9	5.2	Sandy Loam	well	Ferralsol	Sols ferralitiques
34	196	2.3	6.1	Sand	poor	Luvisol	Sol ferrugineux hydromorphiques
35	234	4.4	5.8	Sandy Loam	well	Lixisol	Sol ferrugineux lessivé avec concretions
36	234	4.4	5.8	Loamy Sand	well	Lixisol	Sol ferrugineux lessivé avec concretions
37	202	4.3	5.5	Loamy Sand	well	Luvisol	Sol ferrugineux peu lessivé
38	156	4.9	5.7	Loamy Sand	well	Lixisol	Sol ferrugineux lessivé avec concretions

[a] IUSS Working Group WRB (2014)

(LAI), and a crop parameter for converting energy to biomass. The potential plant growth is driven by photosynthetically active radiation. The amount of solar radiation captured by the crop is a function of LAI, and the amount of solar radiation converted into plant biomass is a function of the crop-specific radiation use efficiency. The daily potential biomass is decreased by stresses caused by water shortage, temperature extremes, nutrient insufficiency, and soil aeration inadequacy. The daily potential biomass is decreased in proportion to the severity of the most severe stress of the day. The EPIC model simulates the effects of temperature on crop yield mainly in two ways. First, the daily potential biomass is reduced by temperature stress, as mentioned earlier. Second, EPIC uses heat unit accumulation to determine phenological development and the duration of the crop cycle. Heat units are calculated daily as the difference between mean air temperature and a crop-specific base temperature and accumulated over time from planting to maturity. In addition, temperature is a determinant of soil evaporation and crop transpiration. Hence, it affects the availability of soil moisture that sustains crop growth. The EPIC model simulates the effects of precipitation on crop yield using a concept of water stress. When crop water demand exceeds soil moisture supply, a water stress day occurs and potential crop yield is reduced by a certain amount. In this study, a calibrated EPIC model (version 3060) for yam for the study region has been used for simulating the effect of climate change on its production (Srivastava et al. 2012). The harvest index value (0.91) used for yam in this study was measured in field experiments conducted in the studied region (Srivastava and Gaiser 2008). EPIC dynamically accounts for soil C interactions in response to land use change, soil management, and climate change, and long-term field experiments have verified reasonable precision in representing these interactions in many regions of the world (Izaurralde et al. 2006).

In order to test the sensitivity of the model to different cardinal temperatures, daily stress index to changes in daily mean temperature and to crop optimum temperature has been calculated between reference run (1961–2000) and climate scenario (2011–2050). Mean

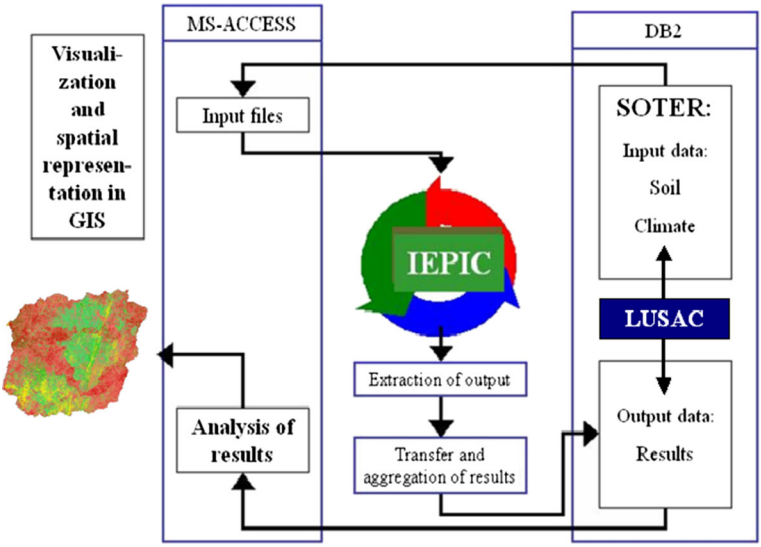

Fig. 1 Workflow and aggregation procedure for the upscaling of EPIC simulation results to the sub-basin and district level

change in temperature was approximately 2 °C which did not affect the temperature stress index for biomass production of yam (Fig. 2). This could be attributed to the following reasons: (i) The daily temperature of reference runs (i.e., time horizon 1961–2000 and 2001–2050) are close to the optimum temperature of yam (Fig. 2), (ii) on most of the days during the growing period of yam, there are the other daily stress factors (water stress) which are higher than the temperature stress (data not shown).

2.3 Climate change projection

The input parameters for the climate scenarios were provided by Paeth et al. (2008) using the regional climate model REMO driven by the IPCC SRES scenarios A1B and B1. For the purpose of model inter-comparison, additional outputs of two other RCMs namely HADR M3P and SMHIRCA were used (Hewitt and Griggs 2004; ENSEMBLES 2010). REMO is a regional climate model that is nested in the global circulation model European Centre

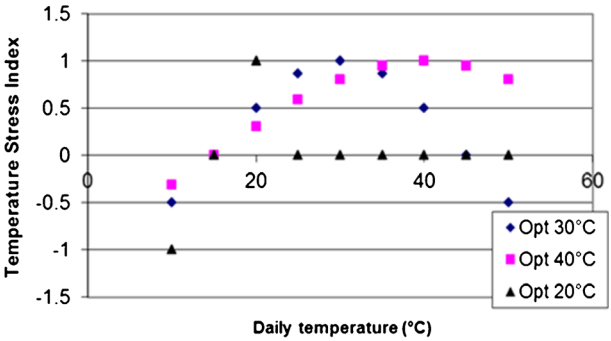

Fig. 2 Temperature stress index under variable temperature regimes

Hamburg Model/Max Planck Institute ocean model (ECHAM5/MPIOM). The other two regional climate models, HADRM3P and SMHIRCA, were driven by the GCM Hadley Centre Coupled Model (HADCM3Q0). The advantages of the new set of REMO simulations are (1) a comparatively high resolution of 0.5°, (2) the consideration of spatial patterns of future land use change, and (3) a transient forcing from 1960 to 2000 and three ensemble runs for two scenarios from 2011 to 2050, reflecting the uncertainties due to climate model structural uncertainty. The output of the HADRM3P and SMHIRCA simulations has approximately the same resolution with transient forcing from 1960 to 2050, but land use changes were not taken into account. For these two RCMs, only output from the A1B SRES scenario was available, which was considered to be sufficient for model inter-comparison as differences between models (e.g., for precipitation) were considerably higher than differences between SRES scenarios.

In the initial REMO runs, the model systematically underestimated the amount and variability of rainfall over West Africa including a shift in rainfall distribution toward weaker events and fewer extremes. To address this issue, model output statistics (MOS) were applied in order to adjust the rainfall data using other near-surface parameters such as temperature and sea level pressure wind components (Paeth et al. 2008) (Fig. 3). In order to transform the MOS-corrected regional mean precipitation from REMO to a local pattern of rain events, a weather generator (WEGE) was applied and produced virtual station data (for details, refer to Srivastava et al. 2012). A cross-validated multiple regression analysis was used in order to adjust monthly data to the climatic research unit (CRU) observational dataset.

2.4 Validation and simulations performed in the study

A total of four climate scenarios based on A1B and B1 emission scenarios with different RCM output has been simulated in this study: the baseline period (1961–2000) with simulated historical data and the time horizon (2011–2050) under IPCC SERES A1B and B1 scenario conditions. For the baseline simulations, the CO_2 concentration was set at 350 ppm as ambient. The effect of increased CO_2 concentrations on yam yield in future time horizon under the IPCC scenarios has not been analyzed to avoid one more factor of uncertainty in response to climate change as it is well known that there is large uncertainty in the CO_2 fertilization effect (Gornall et al. 2010).

Crop management was defined in the simulations according to the prevailing, traditional field activities for long cycle varieties of yam which are dominant in the study region. The start

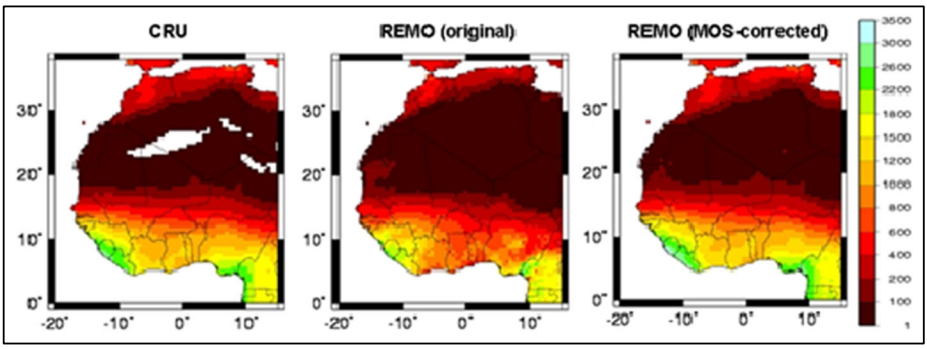

Fig. 3 Long-term mean pattern of observed annual precipitation in West Africa from observations (CRU, New et al. 2002), original REMO output, and REMO output corrected by MOS

and end of the growing season were set to February and December, respectively. Plant density was set at 0.88 plants m^{-2} (Srivastava and Gaiser 2010). Potential heat units (PHUs) were estimated as 1,945 °C day using the average of 2 years growing degree days (GDDs) accumulation during the growing season (i.e., planting to maturity) for yam. Switch grass (*Panicum virgatum* L.) was used as a fallow crop for the baseline and scenario simulations with the climate data derived from REMO, SMHIRCA, and HADRM3P regional climate model. The start and end period of the growing season of fallow crops were set to March and February, respectively. Replanting was done every year to mimic the process of re-growth after the dry season. Plant density was 10.0 plants m^{-2} with PHU of 5,000 °C day.

3 Adaptation strategies explored

We tried to explore specific climate change adaptation strategies for yam under different climate scenarios produced by different regional climate models (REMO A1B, B1; SMHI RCA A1B; and HADRM3P A1B). Firstly, planting date of yam was shifted by delaying 30 days ($S_{0+30,}$) with respect to the baseline, S_0 being the original planting date. Secondly, hypothetical yam cultivar with prolonged vegetative period under climate change scenarios was tested which is controlled by adjusting the growth parameter GDDs in the EPIC model. A crop cycle is determined by the sum of GDDs that it accumulates during the growing season until the concerned crop reaches maturity. To analyze the impact of GDDs, the total temperature sum to maturity was increased by 15 % and its effect on crop yield was estimated. Thirdly, response of the crop to climate change was also evaluated under optimum irrigation supply and fertilizer application.

4 Results

Under the A1B scenario, some parts of tropical Africa may warm by more than 3 °C until 2050, whereas under B1 scenario, the warming pattern is very similar, but the amplitudes are generally 1 °C lower. The absolute annual mean temperature is slightly lower in the HADR M3P and SMHIRCA simulations, but the temperature increase until 2050 is similar to the REMO output (Fig. 4). For the full domain, the regional climate model REMO for the time horizon 2041–2050 simulates an average annual precipitation decrease of 37 and 31 % under IPCC SERES A1B and B1, respectively, relative to the baseline period (1961–2000) (Fig. 5). In contrast, the mean annual precipitation in the period 2041–2050 decreases in the SMHIRCA model simulations only by 7 %, and in the HADRM3P simulations, it increases by 6 % in A1B scenario. As per Fig. 5, REMO and SMHIRCA simulate a gradual decrease of precipitation toward 2050. In the REMO model, some acceleration in the decrease of precipitation toward the middle of the century, consistent with the temporal evolution of climate change signals in longer term global climate model projections from the latest IPCC report.

In order to analyze the effect of climatic variables (temperature and rainfall) solely on the yam yield, baseline and future scenario simulations were performed only with ambient CO_2 concentration (350 ppm). The effect of the climate scenarios on yam yield until 2050 is shown in Fig. 6. As per the output of the climate models, yam yield shows a definite reduction in the study region within the time slice 2021–2050 (Fig. 6). The decrease is more pronounced with the output of the REMO model compared to SMHIRCA and HADRM3P model output. According to Fig. 6, in the climate scenarios derived from the REMO model, the yield of yam would be further reduced significantly in the Upper Ouémé basin (Benin Republic) in the

decade 2041–2050 compared to the baseline period (1961–2000) which accounts for about 33 and 27 % yield loss under IPCC SERES A1B and B1, respectively. For SMHIRCA and HADRM3P under A1B scenario, it accounts for 19 and 18 % decline, respectively (Srivastava et al. 2012).

The simulation of yam yield including different adaptation measures has shown alleviation of climate change impacts in many cases when compared to baseline yield and to the yield estimates without adaptation measures (Table 2). Delay in planting and using the longer maturity cultivar was not able to offset the detrimental effect of climate change under all the scenarios analyzed with an exception of HADRM3P A1B scenario where an increase of 7 and 18 % yam yield has been estimated by delayed planting (by 30 days) and using late maturing cultivars respectively, though not substantial.

5 Discussion

The highest decline in yam yield under REMO simulation output (Table 2) appears not to be due to increase in temperature as projected average temperature is still under optimum temperature required for yam but appears to be driven by the heavy reduction in precipitation for the time horizon 2041–2050 (Fig. 5) compared to the other two RCMs, HADRM3P, and SMHIRCA, respectively. These results underline the need to narrow down the uncertainties related to the projections of precipitation from the climate models to be able to analyze impact of climate change more reliably and with more confidence. Here, in our simulations, one model predicts sharp decrease of precipitation (e.g., REMO), other predicts mild decrease (e.g., SMHIRCA), while HADRM3P model predicts an increase in precipitation. Thus, using a suite of climate models to quantify the uncertainty remains the only possible strategy. However, defining the best models based on evaluation of their behavior over current climate does not ensure robust climate projections (Cook and Vizy 2006). Among the adaptation strategies tested for alleviating the negative impact of climate change on yam yield, delayed

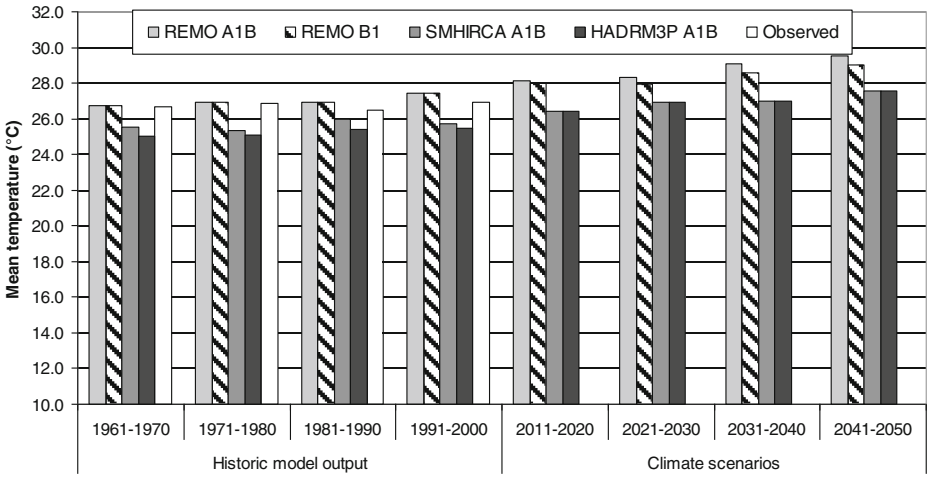

Fig. 4 Comparison of the output of mean annual temperature for the period 1961 to 2050 from three regional climate models (REMO driven by ECHAM5, SMHIRCA, and HADRM3P driven by HADCM3Q0) with observed data (1961–2000) in the Upper Ouémé basin

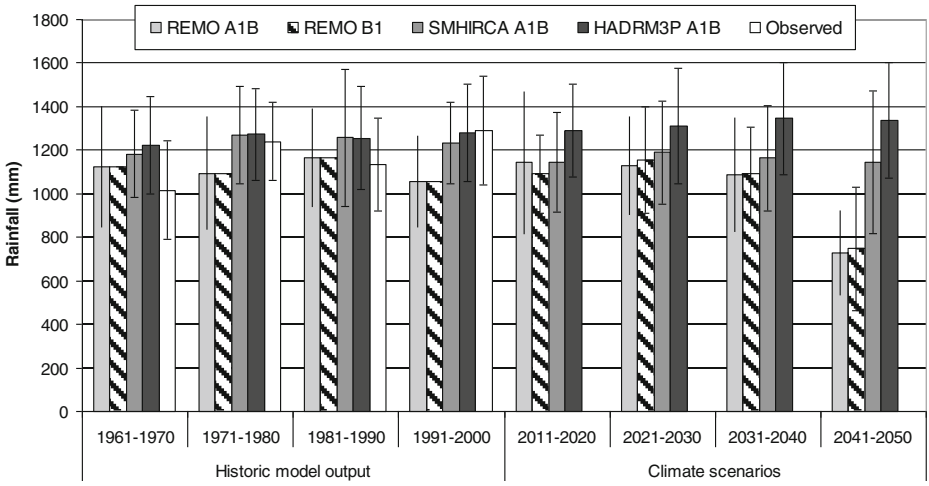

Fig. 5 Comparison of the output of mean annual rainfall for the period 1961 to 2050 from three regional climate models (REMO driven by ECHAM5, SMHIRCA, and HADRM3P driven by HADCM3Q0) with observed data (1961–2000) in the Upper Ouémé basin

planting and use of longer maturity yam cultivar showed positive response only under HADR M3P A1B scenario. This could be attributed to the fact that the mean annual precipitation in the period 2041–2050 in HADRM3P simulations increases by 6 % hence water being not the limiting factor which is not the case with other two RCMs considered. REMO for the time horizon (2041–2050) simulates an average annual precipitation decrease of 37 and 31 % under IPCC SERES A1B and B1, respectively, relative to the baseline period (1961–2000), and SMHIRCA model simulations estimates a decrease in tune of 7 % (Fig. 5).

The most robust improvements of yam yield have been realized by substituting traditional yam cultivars with a late maturing cultivar along with irrigation and fertilizer application.

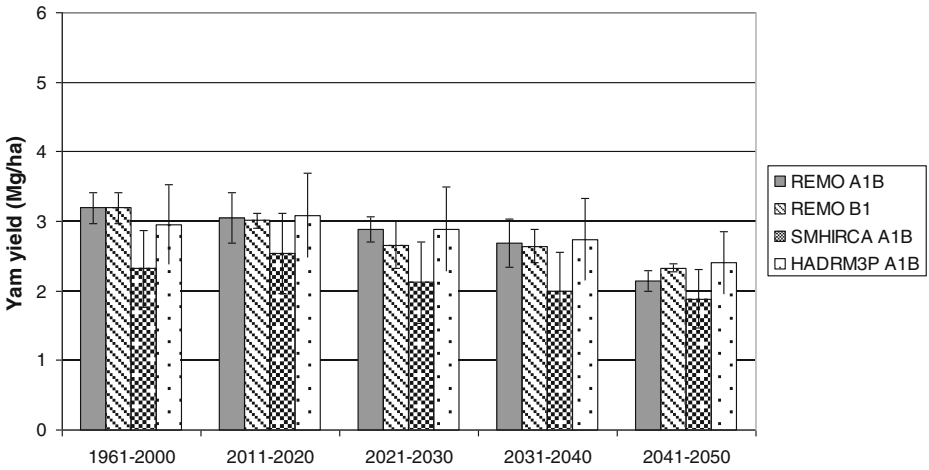

Fig. 6 Comparison of yam yield (Mg dry matter ha^{-1} a^{-1}) in the whole Upper Ouémé basin under IPCC SERES scenarios from three regional climate models (REMO driven by ECHAM5, SMHIRCA, and HADRM3P driven by HADCM3Q0) under ambient CO_2 concentration (350 ppm) in the atmosphere without adaptation

Table 2 Yam yield (Mg dry matter ha^{-1} a^{-1}) in terms of absolute difference with and without adaptation strategies compared to baseline period in the whole Upper Ouémé basin under IPCC SERES scenarios from three regional climate models (REMO driven by ECHAM5, SMHIRCA, and HADRM3P driven by HADCM3Q0)

Yam yield with adaptation strategies explored time period (2041–2050)						
	Baseline Yam yield (Mg/ha) time period (1961–2000)	Yam yield (Mg/ha) without adaptation time period (2041–2050)	Delayed planting by 30 days	Late maturing cultivar	Fertilizer + Irrigation	Fertilizer + Irrigation + Late maturing cultivar
REMO A1B	3.1	−1	−0.8	−0.9	−0.1	0.5
REMO B1	3.1	−0.8	−1.3	−1.2	−0.2	0.4
SMHIRCA A1B	2.3	−0.4	−0.3	0	0.3	0.7
HADRM3P A1B	2.9	−0.5	0.2	0.5	0.8	1.5

Under HADRM3P A1B and SMHIRCA A1B scenario, a relative gain of 49 and 29 % over baseline yield has been estimated, respectively. Whereas, under REMO A1B and B1 scenarios, the gain is in the magnitude of 14 and 11 %, respectively (Fig. 7 and Table 2).

The late maturing cultivars may benefit from the prolonged growth cycle under all climate scenarios and model outputs. Cook and Vizy (2012) recently reported that in Benin Republic, the growing season days will be increased by 5–10 % (1–2 weeks) for the time window 2041–2060. Hence, adaptation strategy of using late maturing cultivar corroborates with this report.

The results obtained in this study demonstrates that the increase in temperatures until 2040s which is common to most climate model outputs for the sub-humid tropics would not constitute a serious problem to the yam production because the optimal temperature for growth of yam is between 25 and 30 °C, depending on the species of yam. As the optimum temperatures of other important tuber and root crops like cassava and sweet potato are also in the range of 25 to 30 °C (CIRAD 2002), this conclusion may hold for all tuber and root crops dominating the root and tuber-based cropping systems in the savannahs of sub-humid

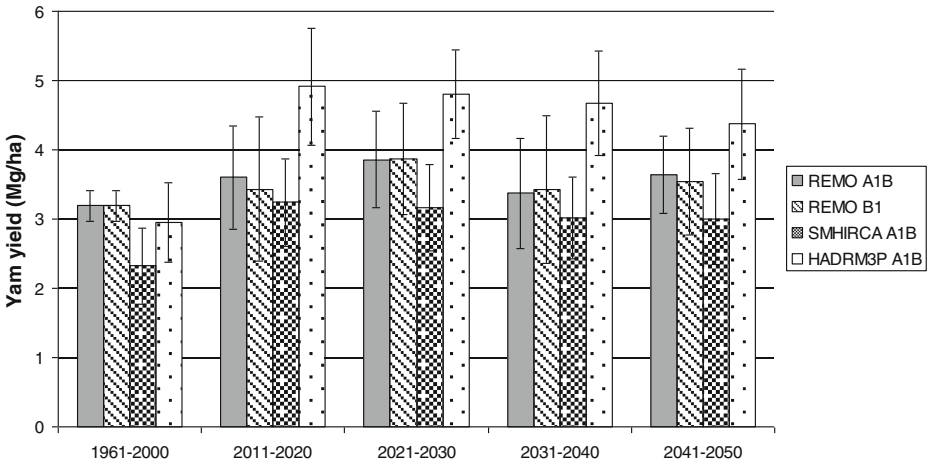

Fig. 7 Comparison of yam yield (Mg dry matter ha^{-1} a^{-1}) in the whole Upper Ouémé basin under IPCC SERES scenarios from three regional climate models (REMO driven by ECHAM5, SMHIRCA, and HADRM3P driven by HADCM3Q0) under ambient CO_2 concentration (350 ppm) in the atmosphere with best adaptation strategy

tropics. The annual average temperature across Ouémé basin is 26.8 °C which is within the range of the optimal temperature required for yam growth and development during the crop growing period. Therefore, reduction in yam yield is not explainable by the change in temperature but must be due to a decline in precipitation (Fig. 5) eventually translating into frequent dry spells, although other climatic factors may also play roles.

Nakicenovic and Swart (2000) also pointed out that a significant impact in terms of the direct fertilization effect of CO_2 cannot be expected before 2050 when CO_2 is likely to reach twice the preindustrial level. Masutomi et al. (2009) also revealed in their findings that the large uncertainty in the rice production estimates was caused by the uncertainty in the CO_2 fertilization effect which was comparable to those caused by the process/parameter uncertainty in the GCMs.

6 Limitations

Among the assumptions made in the simulation study, model calibration was carried out based on the field experiment data of only one yam variety, which generally makes available reference data for large areas. Hence, this study can be significantly refined by interacting with local experts, so that well-adapted cultivars could be simulated as opposed to the idealized types simulated within this exercise. Production systems were abstracted at the level of a single crop, ignoring possible interactions within crop rotations. If cropping systems were analyzed instead, crop performance in a given simulation unit would result from its performance in different rotations and under different inputs of resources. The effect of certain climatic extremes are not taken into account, such as the impact of intense heat during particular development stages which may lead to total crop failure, but this is known only for cereal crops.

7 Conclusion

We investigated different adaptation options which could offset climate change impacts on yam productivity in the sub-humid savannah of West Africa, which is typical for savannahs of the sub-humid tropics in South America, Africa, and Asia in terms of climate and soil conditions. The presented differences in tuber yields between adapted and current yam cultivars indicate that promoting cultivars with longer maturity, combined with irrigation and nutrient supply could help in alleviating potentially detrimental effects of the expected increases in average temperature over the growing cycle. As this general increase in average temperature is common to all climate scenarios (independent of the GCM and downscaling approach) and is expected throughout the savannahs of the sub-humid tropics, the adaptation options presented here can be applied to similar tropical environments and to other tuber crops, which have comparable optimum temperature ranges as *Dioscorea* species. Two aspect that requires future attention are (1) the analysis of extreme temperatures which is known to lead to complete crop failure with some cereal crops when occurring in sensitive development stage but has not yet been investigated in tuber and root crops and (2) the evaluation of the impact of increasing average temperatures on the activity and composition of pest and disease populations which could negatively affect the yield of tuber and root crops.

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