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IMPLICATIONS OF FUTURE CLIMATE CHANGE ON AGRICULTURAL PRODUCTION IN TROPICAL WEST AFRICA

EVIDENCE FROM THE REPUBLIC OF BENIN

vorgelegt von

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Implications of future climate change on agricultural production in tropical West Africa: evidence from the Republic of Benin

Auswirkungen des zukünftigen Klimawandels auf die landwirtschaftliche Produktion in tropischen Westafrika: eine Fallstudie für die Republik Benin

Conséquences des changements climatiques futures sur la production agricole en Afrique de l'Ouest tropicale : étude de cas en République du Bénin

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“Thus, human beings are now carrying out a large scale geophysical experiment of the kind that could not have happened in the past… Within a few centuries we are returning to the atmosphere and oceans the concentrated organic carbon stored in sedimentary rocks over hundreds of millions of years.”

—Dr. Roger Revelle, Tellus *IX, 1957*

“Aveugle à la nécessité de coopérer avec la nature, l'Homme passe son temps à détruire les ressources de sa propre vie. Encore un siècle comme celui qui vient de s'écouler et la civilisation se trouvera en face de la crise finale. Bien que la conscience terrifiée du danger tende à se faire de plus en plus largement sentir… il n’en reste pas moins que nulle part on n’est encore maître de la situation… Le moment ne serait-il pas venu de reconnaître qu'aucune stabilité politique n'est possible si les besoins alimentaires fondamentaux d'un peuple ne peuvent arriver à être satisfaits?”

—Henry Fairfield Osborn Jr, Our Plundered planet, 1948

I dedicate this thesis to the memory of my mother Cyrilla Félicité.
So far she seems, so close she is.
I wish her God's grace.

Abstract

Environmental interlinked problems such as human-induced land cover change, water scarcity, loss in soil fertility, and anthropogenic climate change are expected to affect the viability of agriculture and increase food insecurity in many developing countries. Climate change is certainly the most serious of these challenges for the twenty-first century. The poorest regions of the world – tropical West Africa included – are the most vulnerable due to their high dependence on climate and weather sensitive activities such as agriculture, and the widespread poverty that limits the institutional and economic capacities to adapt to the new stresses brought about by climate change. Climate change is already acting negatively on the poor smallholders of tropical West Africa whose livelihoods dependent mainly on rain-fed agriculture that remains the cornerstone of the economy in the region. Adaptation of the agricultural systems to climate change effects is, therefore, crucial to secure the livelihoods of these rural communities. Since information is a key for decision-making, it is important to provide well-founded information on the magnitude of the impacts in order to design appropriate and sustainable adaptation strategies.

Considering the case of agricultural production in the Republic of Benin, this study aims at using large-scale climatic predictors to assess the potential impacts of past and future climate change on agricultural productivity at a country scale in West Africa. Climate signals from large-scale circulation were used because state-of-the art regional climate models (RCM) still do not perfectly resolve synoptic and mesoscale convective processes. It was hypothesised that in rain-fed systems with low investments in agricultural inputs, yield variations are widely governed by climatic factors. Starting with pineapple, a perennial fruit crops, the study further considered some annual crops such as cotton in the group of fibre crops, maize, sorghum and rice in the group of cereals, cowpeas and groundnuts belonging to the legume crops, and cassava and yams which are root and tuber crops. Thus the selected crops represented the three known groups of photosynthetic pathways (i.e. CAM, C3, and C4 plants).

In the study, use was made of the historical agricultural yield statistics for the Republic of Benin, observed precipitation and mean near-surface air temperature data from the Climatic Research Unit (CRU TS 3.1) and the corresponding variables simulated by the regional climate model (RCM) REMO. REMO RCM was driven at its boundaries by the global climate model ECHAM 5. Simulations with different greenhouse gas concentrations (SRES-A1B and B1 emission scenarios) and transient land cover change scenarios for present-day and future conditions were considered. The CRU data were submitted to empirical orthogonal functions analysis over the north hemispheric part of Africa to obtain large-scale observed climate predictors and associated consistent variability modes. REMO RCM data for the same region were projected on the derived climate patterns to get simulated climate predictors. By means of cross-validated Model Output Statistics (MOS) approach combined with Bayesian model averaging (BMA) techniques, the observed climate predictors and the crop predictand were further on used to derive robust statistical relationships. The robust statistical crop models perform well with high goodness-of-fit coefficients (e.g. for all combined crop models: $0.49 \leq R^2 \leq 0.99$; 0.28 ≤ Brier-Skill-Score ≤ 0.90).

Provided that REMO RCM captures the main features of the real African climate system and thus is able to reproduce its inter-annual variability, the time-independent statistical transfer functions were then used to translate future climate change signal from the simulated climate predictors into attainable crop yields/crop yield changes. The results confirm that precipitation and air temperature governed agricultural production in Benin in general, and particularly, pineapple yield variations are mainly influenced by temperature. Furthermore, the projected yield changes under future anthropogenic climate change during the first-half of the 21st century amount up to -12.5% for both maize and groundnuts, and -11%, -29%, -33% for pineapple, cassava, and cowpeas respectively. Meanwhile yield gain of up to +10% for sorghum and yams, +24% for cotton, and +39% for rice are expected. Over the time period 2001 – 2050, on average the future yield changes range between -3% and -13% under REMO SRES–B1 (GHG)+LCC, -2% and -11% under REMO SRES–A1B (GHG only),and -3% and -14% under REMO SRES–A1B (GHG)+LCC for pineapple, maize, sorghum, groundnuts, cowpeas and cassava. In the meantime for yams, cotton and rice, the average yield gains lie in interval of about +2% to +7% under REMO SRES–B1 (GHG)+LCC, +0.1% and +12% under REMO SRES–A1B (GHG only), and +3% and +10% under REMO SRES–A1B (GHG)+LCC. For sorghum, although the long-term average future yield depicts a reduction there are tendencies towards increasing yields in the future. The results also reveal that the increases in mean air temperature more than the changes in precipitation patterns are responsible for the projected yield changes. As well the results suggest that the reductions in pineapple yields cannot be attributed to the land cover/land use changes across sub-Saharan Africa. The production of groundnuts and in particular yams and cotton will profit from the on-going land use/land cover changes while the other crops will face detrimental effects.

Henceforth, policymakers should take effective measures to limit the on-going land degradation processes and all other anthropogenic actions responsible for temperature increase. Biotechnological improvement of the cultivated crop varieties towards development of set of seed varieties adapted to hotter and dry conditions should be included in the breeding pipeline programs. Amongst other solutions, application of appropriate climate-smart agricultural practices and conservation agriculture are also required to offset the negative impacts of climate change in agriculture.

Zusammenfassung

In vielen Entwicklungsländern gefährden Umweltprobleme wie die tiefgreifende Veränderung der Landoberfläche, Wasserknappheit, Bodendegradation und der anthropogene Klimawandel die Leistungsfähigkeit der Landwirtschaft und erhöhen so das Risiko von Nahrungsmittelknappheit. Von diesen miteinander verwobenen Bedrohungen ist der Klimawandel im 21. Jahrhundert sicherlich die bedeutendste. Die höchste Vulnerabilität weisen die ärmsten Regionen der Welt – unter anderen Westafrika – auf, sowohl wegen der großen Bedeutung von klima- und wettersensitiven Wirtschaftsektoren wie der Landwirtschaft als auch wegen der verbreiteten Armut. Diese schränkt die staatlichen und wirtschaftlichen Anpassungskapazitäten an die neuen Herausforderungen durch den Klimawandel ein. Westafrikanische Kleinbauern, deren Lebensunterhalt wesentlich vom traditionellen Regenfeldbau – dem Eckpfeiler der regionalen Wirtschaft – abhängt, bekommen die negativen Auswirkungen bereits zu spüren. Die Adaption der agroökonomischen Systeme an den Klimawandel ist eine unbedingte Notwendigkeit für die Sicherung der Lebensgrundlage dieser ländlichen Gebiete. Da Wissen die Basis für Entscheidungen darstellt, sind belastbare Informationen über das Ausmaß der Auswirkungen wichtig, um angemessene und nachhaltige Anpassungsstrategien zu entwickeln.

Am Beispiel der Republik Benin untersucht diese Studie das Potenzial von makroskaligen klimatischen Prädiktoren zur Erfassung und Quantifizierung des potentiellen Einflusses von beobachteten und künftigen Klimaänderungen auf die landwirtschaftliche Produktion eines westafrikanischen Landes. Die Auswirkungen der großskaligen Zirkulation wurden herangezogen, da auch moderne Regionale Klimamodelle (RCMs) Schwierigkeiten haben, klein- oder mesoskalige synoptische und insbesondere konvektive Prozesse überzeugend zu simulieren. Zugrunde liegt die Annahme, dass Schwankungen des landwirtschaftlichen Ertrags in auf Regenfeldbau basierenden landwirtschaftlichen Systemen mit geringen Kapitaleinsatz zu weiten Teilen auf klimatische Faktoren zurückzuführen sind. Untersucht werden die Ananas als perennierende Pflanze sowie einige einjährige Feldfrüchte wie Baumwolle aus der Gruppe der Faserpflanzen, die Getreidearten Mais, Sorghumhirse und Reis, die Hülsenfrüchte Augenbohne und Erdnuss sowie die Knollen- und Wurzelfrüchte Maniok und Yams. Somit repräsentieren die ausgewählten Feldfrüchte die drei bekannten Photosynthese-Wege, nämlich CAM, C3 und C4.

Die vorliegende Studie verwendet historische Ertragsstatistiken der Republik Benin, Beobachtungsdaten der Climate Research Unit für den monatlichen Niederschlag sowie die

bodennahe Mitteltemperatur (CRU TS 3.1) und die entsprechenden Variablen simuliert durch das REMO RCM. Dieses Regionalmodell wird an seinen Rändern durch das globale Klimamodell ECHAM 5 angetrieben. Es werden Modellsimulationen mit unterschiedlichen Randbedingungen im Hinblick auf Treibhausgaskonzentrationen (die Szenarien SRES-B1 und SRES-A1B) und Veränderungen der Landbedeckung (LCC) berücksichtigt. Mittels Hauptkomponentenanalyse werden aus den CRU-Daten für den nordhemisphärischen Teil Afrikas Zeitreihen und räumliche Muster für großskalige Prädiktoren gewonnen. Um mit diesen konsistente Prädiktoren für die Simulationen zu erhalten, werden die Datenfelder des REMO RCMs auf die so gewonnenen Raummuster projiziert. Für die beobachteten Zeitreihen der Prädiktoren und die zeitliche Entwicklung der unterschiedlichen Feldfrüchte als Prädiktant werden mittels eines kombinierten Ansatzes aus kreuzvalidierten Model Output Statistics (MOS) und Bayesian Model Averaging (BMA) Techniken robuste statistische Zusammenhänge erfasst. Die resultierenden statistischen Modelle zeigen gute Performance, beispielsweise gilt für alle erzeugten Modelle $0{,}49 \leq R^2 \leq 0{,}99$ und $0{,}28 \leq$ Brier-Skill-Score $\leq 0{,}90$.

Da das REMO RCM die Hauptcharakteristika des beobachteten Klimas in Afrika erzeugt und daher die interannuelle Variabilität realistisch reproduziert, können mithilfe der zeitunabhängigen statistischen Transferfunktionen Klimaänderungssignale, gewonnen aus den simulierten Prädiktoren, in zu erwartende Veränderungen der Ernteerträge übersetzt werden. Die Ergebnisse bestätigen, dass Niederschlag und bodennahe Temperatur allgemein die landwirtschaftliche Produktion bestimmen und insbesondere die Schwankungen in den Ananaserträgen primär thermisch bedingt scheinen. Weiterhin finden sich unter den simulierten künftigen Klimabedingungen projizierte Ertragsänderungen von bis zu -12,5% für Mais und Erdnuss und -11% , -29% und -33% für Ananas, Maniok und Augenbohne. Zugleich werden Ertragssteigerungen von +10% für Sorghumhirse und Yams, +24% für Baumwolle und +39% für Reis projiziert. Diese Änderungen sind abhängig von den Randbedingungen. Im Mittel betragen die simulierten Änderungen der Erträge während der Periode von 2001 bis 2050 zwischen -13% und -3% für SRES-B1 + LCC, -11% und -2% für SRES-A1B sowie -14% bis -3% für SRES-A1B + LCC für Ananas, Mais, Sorghumhirse, Erdnuss, Augenbohne und Maniok. Daneben finden sich für Yams, Baumwolle und Reis Zuwächse im Ernteertrag, die in Intervallen zwischen +2% bis +7% für SRES-B1 + LCC, +0.1% bis +12% für SRES-A1B und +3% bis +10% für SRES-A1B + LCC liegen. Obwohl die durchschnittliche Veränderung im Ertrag der Sorghumhirse negativ ist, lassen sich auch Tendenzen hin zu positiven Veränderungen feststellen. Die Ergebnisse zeigen zudem, dass die projizierte Zunahme der mittleren

Lufttemperatur die simulierten Ernteerträge stärker beeinflusst als Veränderungen in den Niederschlagsmustern. Weiterhin scheint im Fall der Ananas der simulierte Rückgang im Ertrag nicht auf Veränderungen bei Landnutzung oder Landoberflächenbedeckung im subsaharischen Afrika zurückführbar. Die Erdnuss- und insbesondere Yams- und Baumwollerzeugung werden von den Veränderungen in der Landoberflächenbedeckung, die für die übrigen Feldfrüchte nachteilige Effekte bedeuten, profitieren.

Zukünftig sollten politische Entscheidungsträger wirksame Maßnahmen einleiten, um die fortschreitende Landdegradation sowie alle anderen anthropogenen Prozesse, die zur globalen Erwärmung beitragen, einzuschränken. Biotechnologische Verbesserungen der verwendeten Nutzpflanzen, um an heißere und trockenere Bedingungen angepasste Varianten zu erzeugen, sollten in die bestehenden Aufzuchtprogramme integriert werden. Weiterhin sind unter anderem die Anwendung von geeigneten, klimaintelligenten landwirtschaftlichen Verfahren sowie eine nachhaltige Agrarwirtschaft notwendig, um die Schäden des Klimawandels auf die Landwirtschaft auszugleichen.

Résumé

La durabilité de l'agriculture et la sécurité alimentaire dans beaucoup de pays en développement sont sujettes à des défis environnementaux connexes tels que les changements du climat et du couvert végétal dus aux actions anthropiques, le déficit hydrique et la baisse de la fertilité des sols. Les changements climatiques sont certainement le plus important de toutes ces crises pour le 21ème siècle. Les régions les plus pauvres du monde, comme l'Afrique de l'Ouest, sont les plus vulnérables en raison de leur forte dépendance aux activités sensibles à la variation du climat telle que l'agriculture. En outre l'extrême pauvreté limite également leurs capacités institutionnelles et économiques à s'adapter aux nouveaux stress climatiques. Les changements climatiques ont ainsi un impact négatif sur les pauvres agriculteurs de l'Afrique de l'Ouest tropicale dont les moyens de subsistance dépendent essentiellement de l'agriculture pluviale, base de l'économie. L'adaptation des systèmes agricoles aux effets néfastes des changements climatiques est alors cruciale pour sécuriser les moyens d'existence de ces communautés rurales. L'information étant capitale pour tout processus de prise de décision, il s'avère important de capitaliser des informations fondées sur l'ampleur des impacts afin de mettre en œuvre des stratégies d'adaptation appropriées et durables.

En se basant sur le cas des systèmes de production agricole au Bénin, cette étude vise à utiliser des signaux climatiques à grande échelle pour évaluer les impacts potentiels des changements observés et futurs du climat sur la productivité agricole en Afrique de l'Ouest. La circulation atmosphérique à grande échelle est préférée car les modèles climatiques régionaux (RCM) modernes ne révèlent pas encore parfaitement les processus de convection atmosphérique aux petites échelles (échelle synoptique et méso-échelle). Cette étude se base en général sur l'hypothèse selon laquelle dans les systèmes d'agriculture pluviale à faible utilisation d'intrants agricoles, les variations de rendement sont majoritairement dues à des facteurs climatiques. En plus de l'ananas, une culture fruitière et pérenne, l'étude a aussi considéré certaines cultures annuelles comme le coton dans le groupe des fibres agricoles, le maïs, le sorgho et le riz parmi les céréales, le niébé et l'arachide dans le groupe des légumineuses, et le manioc et l'igname appartenant au groupe des racines et tubercules. Ces cultures ciblées couvrent ainsi les trois types de mécanisme photosynthétique (photosynthèse en CAM, C3 et C4).

L'étude a exploité les données statistiques sur les rendements agricoles au Bénin, les observations pluviométriques et de températures moyennes ambiantes à la surface terrestre extraites de la base de données du Climatic Research Unit de l'université d'East Anglia (CRU TS 3.1) et les sorties du modèle numérique de climat REMO pour les variables climatiques sus-mentionnées. Le modèle climatique régional REMO à haute-résolution était forcé à ses limites latérales avec le modèle de circulation générale ECHAM 5. Des simulations présentes et futures du modèle REMO avec des scenarii variés de concentration des gaz à effet de serre (SRES A1B et B1) et de changements d'occupation des terres (LCC) sont utilisées. Les données CRU sur une partie de l'Afrique dans l'hémisphère Nord sont soumises à une analyse de fonctions orthogonales empiriques afin d'obtenir des séries temporelles de descripteurs du climat observé à grande échelle ainsi que leurs modes de variabilité spatiale. Les sorties du modèle REMO sont ensuite projetées sur ces modes de variabilité spatiale pour dériver les séries temporelles de descripteurs du climat simulé pour le présent et le futur. Les descripteurs du climat observé ont été utilisés ensuite comme prédicteurs en association avec les séries temporelles de rendements historiques des différentes cultures pour dériver des relations statistiques robustes au moyen de régression linéaire multiple avec validation croisée combinée à des techniques d'inférence bayésienne. Les modèles statistiques de productivité agricole ainsi obtenus pour chaque culture indiquent de bonnes performances, avec comme indicateurs pour tous les modèles $0{,}49 \leq R^2 \leq 0{,}99$ et $0{,}28 \leq$ Brier-Skill-Score $\leq 0{,}90$.

Etant donné que le modèle REMO reproduit bien les principales caractéristiques des climats africains et leurs variabilités interannuelles, les fonctions de transferts statistiques précédemment développées sont utilisées pour traduire les signaux des changements climatiques futurs en rendements escomptés. Les résultats obtenus confirment que les précipitations et la température de l'air gouvernent la production agricole en Afrique de l'Ouest en général et au Bénin en particulier. Les variations de rendements de l'ananas sont majoritairement influencées par la température. Les projections des variations futures de rendements dans des conditions de changements climatiques pour la première moitié du 21ème siècle signalent une baisse de 12,5% pour la production du maïs et de l'arachide, et de 11%, 29%, 33% respectivement pour l'ananas, le manioc et le niébé. Dans le même temps, des augmentations jusqu'à 10% sont prévues pour le sorgho et l'igname, 24% pour le coton et 39% pour le riz. De 2001 à 2050 les baisses de rendements prévues pour l'ananas, le maïs, le sorgho, l'arachide, le niébé et le manioc sont en moyenne de 3 à 13% sous les projections climatiques futures de REMO SRES-B1(GHG)+LCC, de 2 à 11% sous REMO SRES-A1B(GHG seulement) et de 3 à 14% sous REMO SRES-A1B(GHG)+LCC. Cependant, pour l'igname, le coton et le riz, les augmentations prévues de rendements agricoles se situent entre 2 et 7% sous REMO SRES-

B1(GHG)+LCC, entre 0.1 et 12% sous REMO SRES-A1B (GHG seulement) et entre 3 et 10% sous REMO SRES-A1B (GHG)+LCC. Pour le sorgho, bien que les résultats suggèrent une baisse des rendements moyens à long-terme, une tendance à l'augmentation de rendements dans le futur est également à noter. Les résultats ont montré aussi que les augmentations de température moyenne de l'air vont plus impacter les rendements agricoles que les changements des régimes pluviométriques. Aussi, les réductions des rendements de l'ananas ne peuvent pas être attribuées aux changements d'occupation des terres qui a lieu à travers toute l'Afrique au Sud du Sahara. Mais, la culture de l'arachide et surtout de l'igname et du coton vont bénéficier de ces changements d'occupation des terres, tandis que les autres cultures seront confrontées aux effets néfastes.

Les décideurs politiques doivent alors prendre des mesures effectives pour limiter les processus de dégradation des terres et toutes les actions anthropiques conduisant à l'augmentation de la température. La biotechnologie est à mettre à contribution pour améliorer les cultivars existants afin de les rendre plus adaptés aux conditions climatiques futurs (résistance à la chaleur et à la sécheresse). Entre autres solutions, l'application de pratiques agricoles appropriées pour une agriculture intelligente face au climat et l'agriculture de conservation sont aussi nécessaires pour réduire les effets négatifs des changements climatiques.

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« Là où il y a une volonté, il y a toujours un chemin »
Guillaume d'Orange

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Acronyms and abbreviations

ABMA	Automatic Bayesian Model Averaging
AOGCM	Atmosphere-Ocean Global Climate Model
AgMIP	Agricultural Model Intercomparison and Improvement Project
AIC	Akaike Information Criteria
AICc	corrected - Akaike Information Criteria
AR4/ AR5	Fourth IPCC assessment report / Fifth IPCC assessment report
BMA	Bayesian Model Averaging
BIC	Bayesian Information Criteria
BSS	Brier-Skill-Score
CAM	Crassulacean acid metabolism
CARDER	Centre Agricole Régional pour le Développement Rural
CGCM	Coupled Global Climate Model
CO_2	Carbone dioxide
CORDEX	Coordinated Regional Climate Downscaling Experiment
CIWARA	Climate Change Impacts on West Africa Agriculture
CRU	Climatic Research Unit – University of East Anglia (UK)
CSA	Climate-Smart Agriculture
DGVM	Dynamical Global Vegetation Model
EOF	Empirical Orthogonal Functions
ESM	Earth System Model
FAO	Food and Agriculture Organization of the United Nations
GCM	Global Climate Model
GDP	Gross Domestic Product
GHG	Greenhouse gases
GPCC	Global Precipitation Climatology Centre
GPCP	Global Precipitation Climatology Project
IDW	Inverse Distance Weighting
IMPETUS	Integratives Management-Projekt für einen effizienten und tragfähigen Umgang mit Süßwasser in Westafrika Integrated Approach to the Efficient Management of scarce Water resources in West Africa (Project)

IMSL	International Mathematics and Statistics Library
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Inter-Tropical Convergence Zone
LCC	Land Cover Change
LUCC	Land Use / Land Cover Change
MAEP	Ministère de l'Agriculture, de l'Elevage et de la Pêche
	Ministry of agriculture, livestock and fisheries
MDG	Millennium Development Goals
MLR	Multivariate Linear Regression
MOS	Model-Output-Statistics
MPI-OM	Max-Planck Institute ocean model
PC	Principal Component
PCA	Principal Component Analysis
R^2	Coefficient of determination
RCM	Regional Climate Model
REMO	Regional Modell
RMSE	Root Mean Square Errors
SCDA	Secteur Communal de Développement Agricole
SRES	Special Report on Emission Scenarios
SRTM	Shuttle Radar Topography Mission
TRMM	Tropical Rainfall Measuring Mission
UN	United Nations
UNEP	United Nations Environment Programme
USGS	United States Geological Survey
WAM	West African Monsoon
WMO	World Meteorological Organization

1 INTRODUCTION

1.1 Motivation and background

Since the second-half of the twentieth century, the pace, magnitude and spatial extent of anthropogenic changes to the earth system functioning are unprecedented (Lambin et al 2001; Christensen et al 2007). Global warming, biodiversity losses, genetic erosion, loss in soil fertility, human induced land cover changes, water scarcity and climate change are among the new complex environmental issues (Kolawole et al 2011; Yegbemey 2014).

In many respects, climate change has become the most serious development challenge for the twenty-first century. Globally, extreme weather and climate events have received much attention in recent decades (Anderegg et al 2010; Kolawole et al 2011; IPCC 2013; Cook et al 2013). Observation has shown that the global average near-surface air temperature increased by 0.74°C/century during the last century (Hulme et al 2005; Kotir 2011; Salvi et al 2011) and is projected to further increase by 1.5°C – 4.5°C by 2050 (Baskin 1993; Peng et al 2004). Accumulated evidence demonstrates that the major cause of this global warming is the increase in atmospheric greenhouse gases (GHG) concentrations in particular atmospheric carbon dioxide (atmospheric CO_2) (IPCC 1990; IPCC 1995; IPCC 2001; IPCC 2007; IPCC 2013).

Although in its recent economic activity the African continent has not contributed too much to the release of carbon dioxide to the atmosphere through combustion of coal, there are evidences that the African land mass is warming faster than the global average (Christensen et al 2007; Niang et al 2014). The accelerated pace of desertification and deforestation of the rain forests and savanna ecosystems are of a major concern in Africa (Semazzi and Song 2001; Ickowitz 2006) and have important implications for the biosphere-atmosphere interactions, and regional and global climate change (Semazzi and Song 2001). Actually Africa contributes to about 20% of the global biomass-burning fires (Redelsperger et al 2006). The African continent is currently hotter than it was a century ago (Hulme et al 2001; Salack 2006a; IPCC 2007). Hulme et al (2005) reported that the mean surface air temperature throughout the African continent increased on average by about 0.5°C/century during the 20th century. Several studies reported that during the last century the African continent, especially the West African region, had witnessed long periods of drought that negatively impacted on the ecosystems, the population and the economic activities they rely on for their livelihoods (Hulme 1992; Mahé and Olivry 1995; Bricquet et al 1997; Servat et al 1999; Nicholson et al 2000; Nicholson 2001; L'HÔTE et al 2002; Nicholson 2013). Recently the widespread floods in 2007 with its severe economic consequences again drew attention to the great vulnerability of the African continent to extreme climatic and meteorological events (Levinson and Lawrimore 2008; Paeth et al 2011a; Braman et al 2013).

A number of studies concluded that sub-Saharan Africa, a domain of special concern in the International Coordinated regional Climate Downscaling Experiment (CORDEX) program (Giorgi et al 2009; Giorgi et al 2012; Kim et al 2013), is a hotspot of climate change (Boko et al 2007; Wheeler and Kay 2010; Daccache et al 2014; Müller et al 2014). An average of 2.1°C increase in mean near-surface air temperature is expected across sub-Saharan Africa by 2050 while rainfall projections are highly variable in space and time (Cairns et al 2013). The drier subtropical regions will warm more than the moister tropics. Many regions will suffer from droughts and floods with greater frequency and intensity (Christensen et al 2007; Kotir 2011). Many of the consequences of this climate change are already apparent and felt across vital economic sectors including agriculture (Maddison 2006; Kolawole et al 2011; Kotir 2011; Ofuoku 2013; Juana et al 2013; Bello et al 2013; Niang et al 2014; Sanfo et al 2014).

It is now on record that climate change is already acting negatively on the poor smallholders of tropical West Africa whose livelihoods depend mainly on rainfed agriculture that remains the cornerstone of the economy (Kurukulasuriya et al 2006; Kotir 2011; Jalloh et al 2013b). As of 2010 Western Africa is home to 332.69 million people which represents 29.3% of the continent population (ADB and ADF 2011). In this region over 60% of the inhabitants lives in rural areas and is involved in agriculture (ECOWAP 2008; Shah et al 2008; Kotir 2011). Nearly one-third of the populace of sub-Saharan Africa in general is said to be already at risk of malnutrition and hunger (Slingo et al 2005; Daccache et al 2014; FAO et al 2014). Concomitantly, with the advances in modern medicine resulting in the control of infant mortality and prolong life expectancy the world's population has experienced a net demographic boom (Hillel and Rosenzweig 2013). From around 600 million in early 1800s (UN 2004; Hillel and Rosenzweig 2013), the world's population is projected to stabilize at around 9.3 billion by 2050s (UNDP 2011; Hillel and Rosenzweig 2013). In West Africa the ever growing population is further jeopardizing the future food security. Due to the severe exposure of the economy to climatic variations, the pre-existing poverty and the low economic and institutional capacities to cope with climate change, the vagaries of climate are of great importance to this region (Boko et al 2007; Nicholson 2013; Niang et al 2014) and are therefore acting as an additional threat (Kolawole et al 2011).

Agriculture is directly connected to climate (Sultan et al 2005; Sultan et al 2008; Schlenker and Roberts 2009) which has always been the main source of fluctuation in food production in most developing countries in the tropics (Butt et al 2005; Sivakumar et al 2005; Yengoh 2013; Ray et al 2015). Climate change is now modifying the agronomical risks and thus increasing the uncertainties related to ensuring food security (Salack 2006a; Sultan et al 2008). It is predicted to affect the viability of agriculture (Rosenzweig and Parry 1994; Parry et al 2004; Zhu et al 2005; Lobell et al 2006) and increase food insecurity in many developing countries through its impact on water availability, temperature, atmospheric CO_2 concentration and other atmospheric variables over space and time (Parry et al 2004; Mishra et al 2013). Though atmospheric CO_2 fertilization will enhance photosynthetic activities in the plants the detrimental impacts from the increase in temperature and changing precipitation patterns will likely supersede the benefits from the increasing atmospheric CO_2 concentration (Wassmann et al 2009; Knox et al 2012; Sultan et al 2013; Mishra et al 2013). Thus climate change will impact on millions of people in West Africa who depend on the agricultural sector for employment, livelihoods and food provision (Kotir 2011; Calzadilla et al 2013; Asafu-Adjaye 2014; Müller and Robertson 2014; Myers et al 2014). Considering the projected climate change, smallholder farmers are left with some worries as to which crops to cultivate, with what management, when and where to grow (Rurinda et al 2014). Hence climate change might set back years of efforts to alleviate poverty and increase shared prosperity in Western Africa.

Although in regions like Europe the key issue is to reduce carbon emissions (Agostini et al 1992; Freibauer et al 2004; da Graça Carvalho 2012; Achtnicht 2012; Reckien et al 2014), in Africa there is still concern for adapting the food production systems to the new stress (Niang et al 2014). Adaptation of the agricultural sector to the climate change effects is crucial to secure the livelihoods of rural communities. Since information is a key for decision-making, it is important to provide well-founded information on the magnitude of the impacts in order to design appropriate and sustainable adaptation strategies. Given the scale and importance of agriculture in Western Africa, future climate change projections are to be translated into production expectations if farmers are to benefit. Doing this will increase information relevant to decisions, enlighten agricultural decision-making processes, support targeting the needs of the local population and foster climate risk management in agriculture.

The wealth of studies addressing climate change impacts on agriculture in Africa used climatic information at fine scales (e.g. station or gridpoint level) (Müller et al 2011; Roudier et al 2011; Knox et al 2012; Jalloh et al 2013b; Sultan et al 2013). Owing to the not-perfect integration of mesoscale atmospheric processes in the current generation of coupled global climate models (CGCMs) and regional climate models (RCMs) (Gbobaniyi et al 2014) the present study offer to use more stable and robust climatic information on large scale circulation. The studies conducted so far in West Africa have focused on the most economic food crops grown in the region. For example maize (*Zea mays*) is among the four most important food crops feeding more than one-half of the world population (Baco et al 2007). Yam (*Dioscorea sp.*) ranks as the second most important root and tuber crop in Africa after cassava (Scarcelli et al 2006) and the fourth most important in the world after potatoes, cassava and sweet potatoes (Lev and Shriver 1998; Mignouna and Dansi 2003). More than 90% of the world production of yams comes from West Africa (Lev and Shriver 1998; Mignouna and Dansi 2003; Scarcelli et al 2006). In this region the so-called guinea yams are part of the socio-cultural life, feed more than 60 million people and contribute to generation of incomes from local and international markets (Orkwor et al 1998; Mignouna and Dansi 2003). As well, in response to the demographic growth both the production and consumption of rice (*Oryza sativa L.*) in West Africa and across the whole sub-Saharan Africa have increased since the 1970s (Sié et al 2012; Daccache et al 2014). But some crops like pineapple, which is also economically important, are understudied in the literature devoted to climate change impacts on agriculture in sub-Saharan Africa. Although the bulk of pineapple (*Ananas comosus*) – well-known for its drought tolerance and high water use efficiency– was sourced in West Africa (Rohrbach et al 2003) and this perennial food crop is still economically important in the region and on the world fruit market, there is no scientific evidence as to whether this production can still be sustainable in times of climate change. Focusing on nine economically important crops including pineapple, the present study ambitions to improve the understanding of climate change impacts on agriculture in West Africa with emphasis on the Republic of Benin.

1.2 Problem statement

The Republic of Benin is a West African country in which agriculture is the dominant economic activity. Indeed, the Beninese agricultural sector employs about 70% of the work force, contributes to 39% of the Gross Domestic Product (GDP) (CIPB 2007) and provides about 88% of the country's export earnings (MAEP 2011). The trade of cotton as the main export product alone represents up to 70% of the country's export earnings (Sodjinou et al 2011). Despite these figures, the agricultural sector in Benin is extremely vulnerable to external shocks among which is climate variability and climate change (Paeth et al 2008a; MEHU 2011; Lawin et al 2013;

Baudoin et al 2014). In recent years, interaction with farmers have shown that the effects of climate change are already felt in the agricultural sector (Akponikpè et al 2010; Guibert et al 2010; Agossou et al 2012; Awoye et al 2012; Sanchez et al 2012; Allé et al 2013; Teka et al 2013) and farmers are adapting to them through various endogenous adaptive strategies (Abidji et al 2012; Agossou et al 2012; Baudoin et al 2014). To counterbalance the dependence of the economy on cotton which prices on the international trade market highly fluctuate from year-to-year (Hussein et al 2006) and be also resilient to other external shocks, the country, in 2007 adopted a strategic plan for the revival of its agricultural sector. Hence many crops including pineapple (*Ananas comosus*) were selected for promotion so as to diversify agricultural production, reduce food insecurity and malnutrition, and significantly contribute to exports (MAEP 2011).

Grown in the southern part of the Republic of Benin (Fassinou Hotegni et al 2010), pineapple is the third most important fruit on the World's tropical fruit market (Rohrbach et al 2003). In the last decade, pineapple production in Benin increased more than four-fold (Adossou 2012; Arinloye et al 2012). Studies have also demonstrated that the production of pineapple in Benin is economically profitable (Arouna and Affomasse 2005; Sodjinou et al 2011). Pineapples from Benin are well appreciated and exported to the sub-region and the European market (Arouna and Affomasse 2005; Arinloye et al 2012). This importance justifies the need of focused study. Many studies addressed the potential impacts of projected climate change on various important agricultural commodities (e.g. maize, sorghum, cotton, rice, yam, cassava, cowpeas, groundnuts) in Benin (Paeth et al 2008a; Srivastava et al 2012; Lawin et al 2013; Regh et al 2014). But to date no study has been reported on the impacts of climate change on pineapple production in Benin and across West Africa despite its importance. In fact perennial food crops like pineapple are in general understudied in the literature devoted to climate change impacts in agriculture (Lobell et al 2006). Moreover the few available studies addressing climate change impacts in agriculture in Benin failed to assess separately the relative contribution of temperature and precipitation which may limit the prioritization of adaptation strategies. Thus the present study is a contribution to improve knowledge on climate change impacts in Benin by assessing with uncertainties the attainable crop yields for pineapple and the aforementioned crops in Benin under projected climate change conditions.

1.3 Research objectives

The overall goal of the research reported here is to quantify with uncertainties the potential impacts of future climate change on agricultural production in Benin by means of statistical models that describe the relationships between climate variables and agricultural yields. This objective is based on the hypothesis that in rainfed agriculture with little or no investments in agricultural technology as it is in most sub-Saharan African countries the yield variations are mostly governed by climatic factors. In other words, climate variability and climate change are responsible for changes in agricultural yields.

As dictated by the principal research guideline specific objectives are defined. Thus specifically the study aims at:

(1) developing a statistical crop model to investigate the links between climate variability and pineapple yields

(2) transferring the developed crop model in one above to some other crops grown in the country

(3) translating transient future climate change projections into attainable crops yields

(4) examining separately the effects of the projected changes in precipitation and air temperature on the induced future changes in crop yields

(5) assessing the indirect effects of the projected land use/land cover changes in sub-Saharan Africa on agricultural yield changes.

1.4 Thesis structure

The current contribution is organised in nine chapters which can be grouped in four parts. The first part introduces the question of research (Chapter 1). The second part (Chapter 2) deals with the state-of-the-art climate change projection and climate change impacts assessment in agriculture. It presents the state-of-the art methods for climate information downscaling and impacts modelling in agriculture, and discusses the limitations of the latter methods. The third part of the thesis introduces the study area (Chapter 3), presents data on climate and agricultural yields for predictive purposes (Chapter 4), and describes the development of the coupled climate-crop yield models applied (Chapter 5). Finally the results of the study are presented and discussed in the last part. In Chapter 6 a crop model is evaluated for pineapple in the reference period, and in Chapter 7 this crop model is used to predict future pineapple yield changes in times of climate change. The transferability of this crop model to predict the future yield changes of other crops is investigated in Chapter 8. In the end, the key results are summarized and discussed in Chapter 9 which includes the limitations of the study and policy recommendations.

2 CLIMATE CHANGE AND AGRICULTURAL IMPACT PROJECTIONS IN TROPICAL WEST AFRICA: STATE-OF-THE-ART

In this Chapter the state-of-the-art methodologies for climate change projection and impact modelling in agriculture are presented. It starts by outlining the socio-economic (SRES) scenarios projecting greenhouse gas emissions and the RCP radiative forcing scenarios, followed by the various downscaling and bias correction approaches to the climate information from the circulation models. The future climate change scenarios for tropical West Africa are further summarised. In addition, the approaches for climate change impact projections in agriculture are presented and their advantages and limitations discussed.

2.1 Methodology for developing transient climate change scenarios in tropical West Africa

2.1.1 Current emission scenarios for climate change projection

Atmospheric CO_2 concentration increased from about 280 ppm in 1750 (i.e. pre-industrial time) to the current level of around 379 ppm. Considering all other greenhouse gases the current level of emission is about 430 ppm of CO_2 equivalent. The increase of greenhouse gas concentration could amount up to 550 ppm of CO_2 equivalent by 2035 and lead to more than 2°C rise of the global average temperature (Toulmin 2009). This represents a huge increase when compared to the 20 ppm increase of CO_2 over 8000 years during the pre-industrial time. About two-thirds of the global emissions of greenhouse gases come from the combustion of coal and the remaining one-third from land cover/land use changes (Toulmin 2009).

Further climate projections are strongly dependent on assumptions on future greenhouse gases (GHG) emission or concentration trajectories (Nakićenović et al 2000; Moss et al 2010). Socio-economic GHG emission scenarios are widely used since the release of the fourth Intergovernmental Panel on Climate change IPCC assessment report (IPCC AR4). According to Nakićenović et al (2000) these socio-economic greenhouse gases emission scenarios called SRES scenarios comprises a broad range of the main driving forces of future emissions, from demographic to technological and economic developments. These scenarios are grouped in four different storylines and families (i.e. A1, A2, B1, B2) with the A1 scenario family containing three groups of scenarios that are distinguished by their technological emphasis: fossil intensive (A1FI), non-fossil energy sources (A1T), or a balance across all sources (A1B), while the other scenario families have each only one group of scenario named after the family they belong to. They were used for the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project phase three (CMIP3) (IPCC 2007). In the literature the SRES A1FI, SRES A1B and SRES B1 are commonly referred to as high emission scenario, medium-high emission scenario and low emission scenario respectively. Details on these SRES emission scenarios and their development can be found in Nakićenović et al (2000). Recently, the community of climate modellers stressed the need for alternative greenhouse gases concentration trajectories to provide new inputs of emissions, concentrations and land use/cover for climate models (Moss et al 2010; Harris et al 2014b). Four scenarios of total radiative forcings of the atmosphere in 2100 named representative concentration pathways (RCPs) were developed (i.e. RCP 8.5, RCP6.0, RCP 4.6 and RCP 2.6), and used for the Coupled Model Intercomparison Project - Phase 5 (CMIP5) climate models simulations (Moss et al 2010; van Vuuren et al 2011). For more information on the RCPs the reader is referred to van Vuuren et al (2011). According to Harris et al (2014b) the RCP 8.5 is close to the SRES A1FI, the RCP 6.5 close to SRES B2, RCP 4.5 close to SRES B1, and RCP 2.6 has no equivalent.

2.1.2 Downscaling and bias-correcting climate change information for impact assessment

The primary tool for the assessment of climate change and the projection of its impacts are coupled global climate models (CGCMs) (Giorgi and Mearns 2002; IPCC 2007; Soussana et al 2010; IPCC 2013). In the fourth IPCC assessment report (IPCC-AR4) the CGCMs used were coupled atmosphere-ocean general circulation models (AOGCMs) from CMIP3 which incorporated the interaction between atmosphere and oceans (IPCC 2007; Meehl et al 2007). Current state-of-the-art CGCMs are Earth System Models (ESMs) which include bio-geochemical cycle, with some of them incorporating also interactive aerosols, chemistry and dynamical vegetation components (Flato 2011; Taylor et al 2012; IPCC 2013; Dike et al 2014). About half of the CMIP5 climate models are ESMs (IPCC 2013). The CGCMs compute present-day and future climates under anthropogenic forcing, and provide internally coherent climate dynamics by solving globally climate relevant physical equations (Soussana et al 2010). These coupled global climate models (CGCMs) operate at fairly coarse grid scale of 150 km to 400 km (Paeth et al 2011b; Ju et al 2013). Due to their coarse spatial resolution and an imperfect understanding and representation of key climate dynamics the temporal variability of daily weather sequences from the CGCMs is distorted (Osborn and Hulme 1997; Hansen et al 2006; Soussana et al 2010), as well as the spatial variability of the climatic patterns at regional scale

(Paeth et al 2011b). Hence, some spatial downscaling of the CGCM outputs are required to improve the realism of the projected climates at local and regional scales before driving impact models such as a crop model that operate at finer spatial scale (Challinor et al 2003; Baron et al 2005; Soussana et al 2010). In the literature statistical downscaling, dynamical downscaling and the combination of the two previous approaches (statistical-dynamical downscaling) are reported to improve the accuracy of the climate information from the CGCMs and overcome the spatial scale mismatch issue between CGCMs outputs and the resolution required by impact models (Tian et al 2005; Ju et al 2013).

The statistical downscaling is performed empirically by establishing statistical links between large-scale atmospheric circulation and observed local climatic variables (Mearns et al 1999; Zorita and von Storch 1999; Maraun et al 2010). Perfect prognosis downscaling is based on a developed statistical transfer function between physically meaningful large-scale observational or reanalysis data taken as predictors and local observations (Wilby and Wigley 1997; Murphy 1999; Schmidli et al 2006; Themeßl et al 2011). The developed transfer function is further applied directly to CGCMs to generate regional climate change projections (Schmidli et al 2007; Themeßl et al 2011). Same applies to statistical downscaling by means of Model-Output-Statistics (MOS), except that with MOS the free atmospheric variables used in developing the transfer functions are directly taken from the climate models (Xu 1999; Paeth 2011). In the literature many statistical downscaling techniques have been proposed (Wilby and Wigley 1997; Zorita and von Storch 1999). For a review of progress in statistical downscaling techniques the reader is referred to Maraun et al (2010) and Jacobeit et al (2014). These techniques are generally cheap in time and cost, less computationally demanding, and can be grouped into three main types: (1) multiple regression, (2) weather typing, and (3) stochastic weather generators (Giorgi and Mearns 1991; Wilby and Wigley 1997; Xu 1999; Wilby et al 2002; Fowler et al 2007). Numerous studies have compared the performance of the existing statistical downscaling techniques (Chen et al 2012b; Abatzoglou and Brown 2012; Gutiérrez et al 2013; Hu et al 2013; Gutmann et al 2014; Sunyer et al 2015; Werner and Cannon 2015). Freeware packages such as the Statistical DownScaling Model (SDSM) are even developed to ease the statistical downscaling task for the end-user (Wilby et al 2002; Wilby and Dawson 2013). But the statistical downscaling methods are generally reported to underestimate the variance and poorly represent extreme events (Fowler et al 2007). In fact their outputs are very sensitive to the underlying assumptions (Mearns et al 1997; Mavromatis and Jones 1998; Challinor et al

2009), while unprocessed climate model outputs avoid the need of assumptions and are consistent with atmospheric physics (Challinor et al 2009).

On the other hand, dynamical downscaling relies on limited area high-resolution numerical models called regional climate models (RCMs) that operate at high spatial resolution (10 – 50 km) to refine the transient climate information from CGCMs based on physical equations (Wang et al 2004; Browne and Sylla 2012). The RCMs are often preferred to the statistical downscaling techniques because they account for small-scale dynamical and physical processes in regional climate systems (Wang et al 2004; Laprise et al 2008; Paeth et al 2011b), and can also enable simulation of climate feedback effects at regional scale (Wang et al 2004; Abiodun et al 2008; Abiodun et al 2012; Yu et al 2014). Due to their high spatial resolution they provide a better description of orographic effects, as well as land-sea contrast and land surface characteristics (Maraun et al 2010). But this downscaling approach is very demanding in computational resources (Mearns et al 1999). In recent years there have been a surge of interest in providing high-resolution regional climate change projection in Africa using various RCMs (Paeth et al 2009; Sylla et al 2009; Paeth et al 2011b; Mariotti et al 2011; Hernández-Díaz et al 2012; Laprise et al 2013; Teichmann et al 2013; Mariotti et al 2014). Numerous studies showed that dynamical downscaling significantly improves the representation of precipitation and temperature when compared with their driven CGCMs (Sylla et al 2009; Heikkilä et al 2011; Ju et al 2013). Because new information is added to the RCMs to enable them model sub-grid atmospheric processes, the outcomes of the RCMs may bear statistical properties different from those of the driven CGCMs (Soussana et al 2010).

Despite their considerable advantages in reproducing regional climate, the RCMs still feature systematic model errors (Frei et al 2003; Hagemann et al 2004; Suklitsch et al 2011; Themeßl et al 2011; Nikulin et al 2012; Kim et al 2013; Endris et al 2013; Gbobaniyi et al 2014). Oettli et al (2011) reported that the performance of various RCMs at reproducing the key climatic variables pertinent for agricultural applications in sub-Saharan Africa is questionable. In fact any errors in the climate models may have implications for the simulation of crop growth and development, and hence agricultural yield projections (Baigorria et al 2007; Challinor et al 2009; Berg et al 2010; Salack et al 2012; Ceglar and Kajfež-Bogataj 2012). Thus post-processing of the RCM outputs is still required to correct the model bias and provide optimized climate scenarios for climate change impact research (Themeßl et al 2011; Berg et al 2012; Teutschbein and Seibert 2012). But Ehret et al (2012) argued that the bias correction of RCM outputs as applied is not a valid procedure because: (1) it can alter the climate change signal from climate models as well as the spatio-temporal covariance structures of the corrected atmospheric variables, (2) it violates conservation principles and completely ignores the links and feedbacks among atmospheric variables under climate change conditions, and (3) it is not clear whether the existing bias correction methods are non-stationary in time and the biases themselves are time-invariant. Nevertheless bias correction methods are still applied. The simplest methods to bias correct the RCM outputs are the use of monthly mean correction or the delta change approach, with the latter consisting in solely adding the difference in climatological means between present-day and future simulations of a given atmospheric variable from a RCM to observations of that variable (Themeßl et al 2012; Ehret et al 2012; Räty et al 2014). More complex methods are developed and employed particularly when more improved spatial resolution or station-scale climate information is needed (Paeth and Diederich 2011; Themeßl et al 2011). This gives rise to the combined approach termed statistical-dynamical downscaling (Paeth et al 2011b; Paeth 2011; Martinez et al 2013; Reyers et al 2013; Reyers et al 2015). In the literature various statistical methods often referred to as statistical downscaling and error correction methods (e.g. multiple linear regression methods such as Model-Output-Statistics, multiple linear regression with randomization, analog methods, fitted histogram equalization, quantile mapping, gamma-gamma transformation, local intensity scaling, kernel density distribution mapping) are developed and applied -depending on the atmospheric variables considered- to correct the bias in monthly mean or higher distribution moments of the RCM outputs against observational data (Piani et al 2010a; Piani et al 2010b; Paeth 2011; Themeßl et al 2011; Sunyer et al 2012; Themeßl et al 2012; Gudmundsson et al 2012; Teutschbein and Seibert 2012; Ehret et al 2012; Räty et al 2014; McGinnis et al 2015). Stochastic weather generators are also applied to the RCM outputs (Kilsby et al 2007; Paeth and Diederich 2011; Iizumi et al 2012; Verdin et al 2014; Paxian et al 2014; Lu et al 2015; King et al 2015). But the validation of a statistical downscaling and error correction algorithm under present-day climate does not necessarily imply that its synthetic climate change projections are also valid in the future (Chu et al 2010; Themeßl et al 2011).

2.1.3 Climate change projections in tropical West Africa

In tropical West Africa there is actually a large spatial variation in both precipitation and temperature (Baron et al 2005; Berg et al 2010; Challinor et al 2015). Comparing the projected future changes in precipitation under SRES A1B scenarios (2001-2050) for West Africa from nine RCMs nested in the AOGCMs ECHAM5 and HAdCM3, Paeth et al (2011b) reported a spread of mixed projections as the different RCM simulations largely varied in both the sign and magnitude of changes. For example, under SRES-A1B emission scenario and over the time period 2000-2050 projected future precipitation changes from CSIRO Mark 3 and MIROC 3.2 AOGCMs projections are opposed, with the CSIRO AOGCM projecting from no change to an average of 100 mm/year reduction in the Sahel region and an increase along the coast of Sierra Leone and in Liberia, while the MIROC projections are showing increasing precipitation in the Sahel (an average increase of 50-100 to 100-200mm/year) and pronounced drought in Liberia and parts of Cote d'Ivoire (an average reduction of 200-400 mm/year). But the two AOGCMs agreed well on the direction of changes (i.e. declining precipitation) in the southern parts of the belt from Ghana to Nigeria, with more decrease in precipitation in CSIRO than in MIROC (Jalloh et al 2013b). The fourth IPCC assessment report (IPCC-AR4) also pointed to large uncertainty about the future evolution of precipitation in the Sahel, the Guinean Coast and the southern Sahara throughout the 21st century (Christensen et al 2007), while the fifth IPCC assessment report (IPCC-AR5) talked about low to medium confidence in the robustness of the projected precipitation changes for that region (Niang et al 2014). But a multi-model ensemble revealed for this region a drought tendency, with decreasing precipitation of about 5–20% over the time period 2001-2050 under SRES-A1B emission scenario (Paeth et al 2011b). An increase in the frequency of heavy rainfall events (about 20% probability of having extremely wet season) is also to be expected even in regions where significant reduction in total precipitation amounts are projected (Christensen et al 2007; Toulmin 2009). Regarding temperature, tropical West Africa is projected to undergo fast and significant warming throughout the year like the whole of sub-Saharan Africa, with large uncertainty on the magnitude of the increase. From the fourth IPCC assessment report (IPCC-AR4) using CMIP3 CGCMs, the median mean near-surface air temperature increase by the end of the 21st century under SRES-A1B is projected to be in the range of 3–4°C, and about 1.5 times higher than the global average increase. But in Western Sahara the projected mean temperature increases by the end of the 21st century are even above 4°C (Christensen et al 2007; Niang et al 2014). Both the minimum and maximum temperature are projected to rise, with greater increase for the minimum temperature (Vizy and Cook 2012; Niang et al 2014). The most recent IPCC assessment report (IPCC-AR5) also showed that the median projected mean temperature increases for tropical West Africa during the dry season (from December to February) with CMIP5 CGCMs under RCP 4.5 scenario are in the range of 0.5–1 .5°C by 2016 – 2035, 1– 2°C by 2046 – 2065, and 1.5 – 3°C by 2081 – 2100 relative to the 1986-2005 average, with the Sahel and Saharan regions always warming more than the Guinean Coast (IPCC 2013). CMIP5 multi-model ensemble mean showed that the mean annual temperature increase will be higher than 2°C and 4°C respectively by the middle and end of the

21st century under RCP 8.5 scenario. In general temperature projections for tropical West Africa from CMIP3 (SRES A2 and A1B scenarios) and CMIP5 (RCP4.5 and RCP 8.5) CGCMs are in the range of 3 to 6°C by 2100 (Niang et al 2014). In general, the overall uncertainty in climate change projection arise from three sources. These are: (1) the internal variability of the climate system or "climate noise" (i.e. initial condition uncertainty), (2) the climate model uncertainty (i.e. parameter and structural uncertainties in the model design), and (3) the uncertainty in future emission of greenhouse gases (Hawkins and Sutton 2009; Knutti et al 2010; Hawkins and Sutton 2011; Deser et al 2012; Knutti and Sedláček 2012). Hence to ensure robustness of the climate change signals for impact analysis many scholars recommended the use of multi-model ensembles (with one or more ensemble-runs available for each climate model) which are generally reported to outperform individual models by providing greater consistency and reliability while also compensating for model errors (Hagedorn et al 2005; Zhang et al 2006; Sanchez-Gomez et al 2009; Paeth et al 2011b; Diallo et al 2012; Kim et al 2013). But the question as to what is the most suitable way of combination or metric to assign weights to the individual models (i.e. weighting scheme) while building multi-model ensemble mean still remains. Often, simple averaging is used to combine the models, assuming equal contributions from the individual models (Weigel et al 2010). Many scholars also assigned weights deterministically depending on their metric used to assess model performances (Sansom et al 2013), while others pointed to probabilistic ensemble projection using various Bayesian model averaging techniques or fingerprint scaling (Tebaldi et al 2005; Tebaldi and Knutti 2007; Paeth et al 2008b; Knutti et al 2010; Tebaldi et al 2011).

2.2 Methodology for the projection of climate change impact in agriculture

The projected future changes in the climate and weather patterns have direct implications for agriculture in sub-Saharan Africa including tropical West Africa (Paeth et al 2008a; Roudier et al 2011; Sultan et al 2013; Sultan et al 2014). This is highly evident considering that across sub-Saharan Africa agriculture is at the mercy of climate and weather variations, and these climatic variables are directly inputted to crop production functions (Auffhammer and Schlenker 2014). In recent decades many mathematical models linking environmental variables and management factors to crop yields and production are increasingly reported in the literature (Landau et al 2000). In general these models are classified as: (1) empirical regression-type crop models, and (2) dynamical crop models. In the context of changing climate, these models are used to predict either the possible shifts in agro-climatic suitability of some crops (Tuck et al 2006; You et al

2009b; Jarvis et al 2012; Beck 2013) or agricultural production expectations. In this review interest is put on only the approaches for the projection of climate change impact on production expectations.

2.2.1 Empirical crop models

The empirical crop models reported in the literature devoted to climate change impact on agriculture are statistical crop models based on production functions or Ricardian models (Roudier et al 2011).

- Statistical crop models

The statistical crop models are also referred to as empirical crop models in the literature. They are based on multiple regression and are extensively used to investigate the existing deterministic relationships between climate variables and agricultural outputs (crop yield or production) (Peng et al 2004; Lobell and Burke 2008; Schlenker and Roberts 2009; Welch et al 2010; Maharjan and Joshi 2013; Lobell 2013). According to Lobell and Burke (2008), results from the statistical crop models are in general consistent with studies using the process-based crop models. In the literature many scholars used crop yield as predictand in their regression functions (Paeth et al 2008a; Lobell and Burke 2010) while others preferred to use crop production (Ben Mohamed et al 2002; Duivenbooden et al 2002). Crop yield expresses the production per unit of cropland, whereas production data incorporates information on the spatial extent of cultivated lands which has increased over sub-Saharan Africa to meet the enhanced food demand of a rapidly growing population (Ramankutty 2004; Paeth et al 2008a; Gibbs et al 2010). But Ben Mohamed et al (2002) preferred to use the production data for agricultural impact study in sub-Saharan Africa because it compares better to the population food requirements. As well these scholars stated that the production data are the raw data collected by the official agricultural services at village level after harvest. The cultivated cropland area used in the derivation of the yield data are estimated by farmers themselves and thus are often prone to large estimation errors (Ben Mohamed et al 2002; Duivenbooden et al 2002).

The empirical crop models are said to be fine-tuned models because they are often developed for a specific crop at a specific location (Auffhammer and Schlenker 2014). In these models the approaches used to relate agricultural outcomes to weather/climate are based on time series variation, cross-sectional variation or a combination of the two in a panel setting (Lobell and Burke 2010; Lobell et al 2011b; Auffhammer and Schlenker 2014). The statistical models based on time series variation are said to capture well the behaviour characterising the given location while the cross-sectional and panel data based models assume the same parameter values across locations. But the time series models are often limited by the non-availability of relevant long-term historical datasets particularly in data-sparse regions while the cross-sectional models can aggregate data from multiple locations (Lobell and Burke 2009; Lobell and Burke 2010). Regression functions (e.g. multiple linear regressions, quadratic functions) are used to relate the agricultural outputs (production or yield) to observed data of various climatic variables over time. Long enough observational time series of both the yield and climate datasets are required to establish the relationship between crop yield and climate variations in present-day (Lobell et al 2006; Hertel and Rosch 2010; Zinyengere et al 2013). In these regression-based crop models the time series of yield and climate are often detrended before building the response function (Lobell et al 2006). But some authors avoid using detrended time series and thus include the trend (i.e. linear or non-linear trend depending on the form of the response function) in their regression function between non-detrended yield and climate (Lobell and Field 2007). Many methods are used to remove trend from the time series before evaluating the relationship between climate and yield. A common method is the first-difference time series of yield and climate (i.e. the difference in values from one year to the next) (Lobell and Field 2007; Osborne and Wheeler 2013). According to Lobell and Field (2007) the first differences method minimizes the influence of slowly changing factors such as crop management. This method assumes that changes in yields can be driven by only changes in climate. But it cannot be used when absolute values of the predictors and predictand are required (Osborne and Wheeler 2013). Other methods for detrending include removal of the linear, quadratic or cubic trends (Lobell and Field 2007; Osborne and Wheeler 2013). Once the trend is removed the resulting time series (i.e. the residuals) of yield and climate data are used to develop regression models with the detrended yield data as response variable and those of the climate data as predictors (Lobell and Field 2007).

The climate data used in regression-based crop models are often monthly or seasonal variations of precipitation and mean temperature, total precipitation and mean temperature averaged over crop growing season (Paeth et al 2008a; Schlenker and Lobell 2010). Some studies also made use of maximum and minimum temperature or diurnal temperature range (Lobell 2007). Very few statistical crop models in sub-Saharan Africa included other climatic variables like relative humidity (Paeth et al 2008a), number of rainy days, duration of the rainy season, and anomalies of the sea-surface-temperatures (SST) (Ben Mohamed et al 2002; Duivenbooden et al 2002). In their statistical maize-crop modelling study Lobell et al (2011a) include as climate variables only the sum of growing degree days between 8°C and 30°C during the crop growing season, the sum of growing degree days above 30°C, and the total precipitation for the 21-day period centred on anthesis, a critical period for the growth of maize plants. The observed climate data used to build the statistical crop models often contained measurement errors which may bias the identification of robust climate – yield relationship. An attempt to address that issue of the errors in the observational climate datasets and their effects on the robustness of statistical crop models is documented in Lobell (2013). Ward et al (2014) introduced a new regression-based statistical crop model to overcome the spatial resolution limitation of the traditional statistical model while correcting for both sample selection bias (i.e. bias related to the assumption that the observed yields at a given administrative unit used to develop the statistical relationships are randomly drawn from a population of yields within that administrative unit) and ecological bias (i.e. bias related to the fact that the statistical model used averaged yield and climate data for administrative units and it is assumed that the relationships that hold for grouped data also holds for lower-level units). Their model thus controls for sample selection bias while considering spatial dependency and spatial heterogeneity (Ward et al 2014). The predictor variables in the statistical crop models are sometimes standardised to balance out their unit of variation (Ben Mohamed et al 2002). As well, logarithmic transformation of the agricultural data is sometimes performed and used for the response variable, in particular when the model is fit to data collected across geographical zones (Schlenker and Lobell 2010; Lobell and Burke 2010; Lobell et al 2011a). According to Lobell (2007) the use of logarithmic values instead of the absolute values for the response variable allows also in the case of statistical yield modelling to account for a potential increase of yield variance with rising average yields. In many publications the statistical crop models reported are of the form of linear regressions with least squares estimation of the regression parameters (Paeth et al 2008a; Lobell and Burke 2010). But, based on observed climate variables and historical crop yields it has been found that for most cultivated crops the relationships between yields and weather/climate are nonlinear and concave, especially with respect to temperature (Schlenker and Roberts 2006; Lobell 2007; Schlenker and Roberts 2009; Lobell et al 2011a; Auffhammer and Schlenker 2014). Thus the agricultural impacts of the changes in the climate variables depend on how often and by how much the thresholds will be exceeded (Schlenker and Roberts 2006; Auffhammer and Schlenker 2014). According to Auffhammer and Schlenker (2014) for maize, the threshold for mean air temperature is about 29°C and a little bit higher for soybeans and cotton. Luo (2011) reviewed the temperature thresholds at different phenophases and the effects of extreme temperature on crop yield and yield components for a range of crops including cereal crops (e.g. wheat, barley, maize, rice, sorghum), horticultural crops (e.g. broccoli, citrus, tomato) and legume crops (e.g. beans, groundnuts, soybeans). Therefore the use of quadratic regression functions in the statistical crop models has become an alternative to overcome the issue of the non-linearity of the climate – crop production relationship whenever necessary (Lobell et al 2006; Lobell and Burke 2010). The statistical crop model are often cross-validated using resampling methods such as Jackknife technique (Efron and Gong 1983; Camberlin and Diop 1999) and Bootstrapping (Lobell et al 2006; Lobell 2007; Lobell and Field 2007; Paeth et al 2008a). Details on these cross-validation methods can be found in Von Storch and Zwiers (2004).

For the projections of the future climate impact on agriculture the statistical crop models are forced with climate change projections derived from the climate models (AOGCMs or RCMs) (Paeth et al 2008a) or synthetic climate changes scenarios (e.g. ± 10 or 20% changes in rainfall and, ± 1°C or 2°C changes in mean air temperature) (Ben Mohamed et al 2002; Duivenbooden et al 2002; Lobell and Burke 2010) under the assumption that the estimated statistical transfer functions are stationary in time (Paeth et al 2008a). This stationary assumption has direct implication for the agricultural impact simulations (Challinor et al 2005). But Challinor et al (2005) evidenced the non-stationary of climate-yield correlations over decades. In the same vein, McCarl et al (2008) suggested that the stationary assumption is questionable and should be strictly examined in climate change impact analysis when statistical models are used. In general the statistical crop modelling studies reported in the literature focused on annual crops. Very few studies have addressed the case of perennial crops (Lobell et al 2006). Examples of statistical crop modelling studies in West Africa include those of Camberlin and Diop (1999), Ben Mohamed et al (2002), Duivenbooden et al (2002), Paeth et al (2008a), Lobell and Burke (2010), and Schlenker and Lobell (2010).

In Niger, Ben Mohamed et al (2002) and Duivenbooden et al (2002) based their studies on a stepwise multiple linear regression model to predict the impact of climate change on the production of millet, groundnuts and cowpeas. They used as predictand 30-years of historical production data and time series of 13 climatic predictors including sea-surface temperature (SST) anomalies of the Indian ocean, principal components of SST of the global ocean, and SST of the equatorial Atlantic ocean, standardised time series of the summer-time monthly rainfall amounts (July, August and September, i.e. JAS), the number of rainy days within the rainy season and the length of the season, the maximum and minimum air temperatures of the coldest and warmest months, and the wind erosion factor defined as the number of days during the dry season (October to May) with horizontal visibility lower than 5 km. Assuming constant SST anomalies in the future and reductions in rainfall of 10% and 20% and increase in air temperature of 10% and 20% by 2025 with respect to the 1968-1998 climatology they concluded that due to climate change the productions of millets, groundnuts and cowpeas by 2025 will fall by 13%, 11% to 25 %, and up to 30% respectively. They reported that the SST anomalies are quite important for the assessment of climate change impacts on agriculture in the Sahel regions. Camberlin and Diop (1999) had previously evidenced teleconnections of groundnuts yields in Senegal - a country in the western Sahel - with global modes of SSTs (i.e. global tropical SST mode associated with ENSO, and southern equatorial Atlantic ocean mode, both with one-year lag). Similarly, these authors found significant positive correlations between the groundnut yields and the JAS rainfall amounts. In Benin Paeth et al (2008a) found that between 5 to 20% of the reduction in future agricultural yields by 2025 could be attributed to climate change. In their review of climate change impact studies on agriculture across West Africa Roudier et al (2011) reported a median value of -11% change in future agricultural yields while considering only studies based on statistical crop models.

According to Lobell and Field (2007) although the relative importance of the mechanisms occurring in plant and responsible for yield variations cannot be inferred from statistical crop models, these models still capture the net effect of all processes by which climate influences yields, including the effects of those processes still poorly modelled in some mechanistic crop models (e.g. climate-related influences on crop pest dynamics and diseases, air pollution) (Lobell et al 2006). It is claimed that the important advantage of the empirical crop models lies in the fact that they are transparent and allow credible identification of impacts and model uncertainties through the coefficient of determination and confidence intervals while for process-based crop models the important advantages are said to be their ability to make predictions about counterfactual outcomes and welfare (Chetty 2009; Hertel and Rosch 2010; Zinyengere et al 2013; Auffhammer and Schlenker 2014). Statistical crop models are reliable alternative in climate change impact study for crops for which mechanistic crop models are not yet developed or sufficiently tested (Lobell et al 2006). Other attractive aspects of the statistical crop models are their limited reliance on field calibration data (Hertel and Rosch 2010; Lobell and Burke 2010), their lack of reliance on soil and crop management databases that may not be available or difficult to obtain in data-sparse regions (Lobell 2013). In general, statistical crop models are simple to implement and have minimum data requirements (Ward et al 2014). The statistical modelling approach also allow for uncertainty estimations through resampling techniques (Lobell and Field 2007; Lobell and Burke 2010; Lobell 2013). But while using the statistical crop models for future climate change impact projection the changes in the cropping calendar (e.g. planting and harvesting dates) and the crop varieties grown cannot be considered (Lobell and Burke 2010; Zinyengere et al 2013). As well the direction of causality cannot be attributed (Lobell and Field 2007; Roudier et al 2011; White et al 2011; Zinyengere et al 2013). It is often assumed that climatic variations cause yield changes and not vice versa (Lobell and Field 2007). Furthermore, the changes over time in the crop management are either assumed to be uncorrelated with climatic variations or caused themselves by climate and therefore has no influence on the climate-yield relationship (Lobell and Field 2007).

Statistical crop models often use aggregate values for the climate variables (i.e. average over month, season or crop growing period) and this may hide some aspects of sub-seasonal variations (e.g. long dry spells, heat waves) that are important for crop development and growth at a given area (Porter and Semenov 2005; Welch et al 2010; Lobell and Burke 2010; Lobell et al 2011a; Lobell 2013). In addition, the statistical crop models are sometimes subjected to problem of co-linearity between the predictor variables and low signal-to-noise ratios in the yield and climate data (Sheehy et al 2006; Lobell and Ortiz-Monasterio 2007; Lobell and Burke 2010). According to Lobell and Burke (2010) as many climate impact studies still rely on statistical approaches it is important to investigate the specific conditions under which these models could yield unreliable results, quantify the errors incurred while adopting these models, and evaluate those models in many locations. Besides the sampling uncertainty due to the fact that the statistical crop models are based on finite observation datasets and thus do not perfectly describe the climate – yield relationships, these models are also subject to extrapolation uncertainty (Lobell et al 2006), especially when the models are used to inform the future as the projected future climate may likely exceed the extremes of the historical climate used to generate the statistical crop models (Lobell et al 2006; Paeth et al 2009; Paeth et al 2011b). Other aspects of statistical crop models uncertainty may include the changes in the climatic variables omitted in the models (e.g. extremes temperature or rainfall events, months other than the few selected in the models based on analyses of available climate and yield records) and thus assumed not to be influential to the future yields (Lobell et al 2006). According to Lobell et al (2006), in case the omitted variables are not correlated with the variables included in the statistical models, their omission thus introduces another source of uncertainty in the crop yield projections. Another limitation of the statistical crop models for the projection of climate change impact is the absence of adaptation responses. This is usually overcome by using Ricardian models which may include farm-level adaptation analysis in their translation of crop response to climate into economic outcomes (Zinyengere et al 2013).

- Ricardian models and Structural Ricardian Models

Ricardian models are also used to relate crop production to weather and climate outcomes (Mendelsohn et al 1994; Chen et al 2013). It is a cross-sectional approach operating at farm or farmer's household level and measuring long-term effects of environmental change, especially climate change (Chen et al 2013). Unlike the other approaches that study the yields of specific crops, the Ricardian approach examine how changes in climate variables affect the net crop revenue per unit area or the value of farmland (Mendelsohn et al 1994; Chen et al 2013). Thus the approach is used to assess the economic impacts of climate change on agriculture (Chen et al 2013). But the Ricardian approach is reported to be consistent when net crop revenue instead of farmland value is used (Mikémina 2013). Ricardian approach assumes that farmers choose their production portfolio so as to individually maximise their profit, given the local climate and their farm characteristics (Stage 2010; Chen et al 2013). Considering two climate states A and B, it is assumed that for a specific region if climate change induced a shift from a climate state A to a climate state B the farms in this region will adapt by shifting to the production portfolio chosen by farms elsewhere currently experiencing the climate state B (Stage 2010). The approach allows to simultaneously examine the direct impacts of climate change on different crops, the indirect substitution of different inputs, the introduction of different activities and other adaptations to climate change (Mendelsohn et al 1994; Zinyengere et al 2013). Hence, the Ricardian approach captures farm-level adaptation in its measure of impacts (Seo and Mendelsohn 2008). In fact, in their original paper that introduced the approach, Mendelsohn et al (1994) stated that the traditional crop modelling approach that relies on empirical or estimated production functions tend to overestimate the yield because this approach fail to consider the range of adaptation options or economic substitutions farmers apply in response to economic and environmental changes. Thus this bias inherent to the production functions is corrected in the Ricardian approach by using economic data on the value of land or net crop revenues (Mendelsohn et al 1994). But Cline (1996) and Kelly et al (2005) stated that the Ricardian approach is also limited as it fails to consider price changes and cost of transition from one climate state to another. In addition, the approach is said to have a small bias when aggregate supplies do not change a great deal (Mendelsohn and Nordhaus 1996; Chen et al 2013). It is reported that it measures only the long-equilibrium effect and not short-run transition costs (Sanghi and Mendelsohn 2008; Chen et al 2013). Although the model consider full adaptation it does not provide any insight on the adaptation options used and the impacts of climate change without adaptation. Therefore it may over-estimate the benefit of adaptation (Mendelsohn 2008; Roudier et al 2011). Seo and Mendelsohn (2008) also argued that the Ricardian model does not specify how farmers adapt to climate change, and therefore they developed a novel model called Structural Ricardian Model and applied it to study how African farmers adapt livestock management to climate. According to these authors the Structural Ricardian Model compares the adaptation choices of farmers facing different conditions, and thus explicitly model the underlying farmers' endogenous decisions.

The Ricardian approach relies on multiple regression with a quadratic formulation of climate and a linear form for the other input variables (Mendelsohn et al 1994; Chen et al 2013). Besides data on the climatic variables (e.g monthly mean precipitation, monthly mean temperature and their squared values) direct inputs are data on other environmental variables (e.g. salinity, flood prone, irrigation, soil permeability, moisture capacity, wetland, soil erosion, wind erosion, slope length) as well as sets of socio-economic (e.g. farm prices or revenues, income per capita, farm value) and demographic data (e.g. population density, migration) (Mendelsohn et al 1994). Therefore, like in the statistical crop modelling approach previously described, the statistical relationships in the Ricardian approach are also built on present-day datasets, and these relationships may not hold in the future (Zinyengere et al 2013). Nonetheless, the Ricardian approach has been extensively applied in various studies assessing the economic impacts of climate change on agriculture in many regions/countries across the world, for example in Africa (Gbetibouo and Hassan 2005; Ouedraogo et al 2006; Kurukulasuriya et al 2006; Jain 2007; Mano and Nhemachena 2007; Deressa 2007; Kurukulasuriya and Mendelsohn 2008; Seo and Mendelsohn 2008; Benhin 2008; Seo et al 2009; Molua 2009; Nhemachena et al 2010; Mikémina 2013), China (Liu et al 2004; Wang et al 2009; Chen et al 2013), and Israel (Fleischer et al 2008). In West Africa studies following the Ricardian approach showed that in general climate change will negatively affect net crop revenue under hotter and drier future climate conditions (Kurukulasuriya and Mendelsohn 2008; Molua 2009; Ajetomobi et al 2010; Nhemachena et al 2010), with respectively 7.11% and 15.24% reductions in agricultural added value per hectare in 2025 and 2050 in Togo (Mikémina 2013) while in Burkina-Faso farmers may experience total erosion of their income by 2050 (Ouedraogo et al 2006). But Seo et al (2009) stated that African agriculture is more resilient to climate change while combining livestock and net crop revenue.

2.2.2 Dynamic crop models

The dynamic crop models are also called mechanistic crop models, process-based crop models, biophysical crop growth models, ecophysiological crop models or agronomic crop models. They are based on experiments on crops and incorporate knowledge on fundamental processes occurring in the plants (Landau et al 2000). Similarly to the climate models the mechanistic crop models are also simplified representations of complex physical and biological processes (Salack 2006a). They are also extensively used in climate change impact studies (Bassu et al 2014), and to investigate possible adaptation strategies (e.g. adoption of short-cycle crop varieties, genetic improvement of existing crop varieties, shift in sowing date, changes in crop management) of cropping systems to climate change (Adams et al 1990; Stockle et al 1992; Rosenzweig and Wilbanks 2010; Tao and Zhang 2010; Ewert et al 2011; Akponikpè et al 2011; Boote et al 2011; White et al 2011; McCarthy and Vlek 2012; Tidjani and Akponikpè 2012; Singh et al 2012; Tachie-Obeng et al 2013; Bassu et al 2014). The mechanistic crop models are also used to guide breeding of improved crop varieties for higher yields under current and projected future climate conditions, as evidenced by the study of Singh et al (2012) who used the CROPCRO model to evaluate the genetic traits for improving productivity and adaptation of groundnuts to climate change in India.

The existing mechanistic crop models can be classified into: (1) site-specific crop models which operate at field or plot scale and use detailed input information at that scale (Roudier et al 2011), and (2) large-scale crop models that simulate both spatial and temporal dynamics of agricultural production and related processes (Challinor et al 2004; Bondeau et al 2007; Liu et al 2008; Blanc and Sultan 2015). Application of these mechanistic crop models outside their home domain, per example in sub-Saharan Africa, is sometimes troublesome. In most of these crop models the growth parameters are calibrated for high yielding cultivars in temperate regions for which they are originally developed (Folberth et al 2012). As they do not incorporate the crop varieties grown in most developing countries in sub-Saharan Africa they are thus not well suited, without adjustment of the growth parameters, for crop simulation in this region where low-yielding cultivars are still grown (Gaiser et al 2010b; Andersson et al 2011; Folberth et al 2012). But there is still a wealth of studies on climate change impact and adaptation in sub-Saharan Africa including West Africa using both field scale and large scale mechanistic crop models. Field scale crop models used in crop simulations in sub-Saharan Africa include (but not limited to) the Environmental Policy integrated Climate (EPIC) model designed to simulate more than 100 crops using a unified approach (Adejuwon 2005; Gaiser et al 2010a; Gaiser et al

2011; Srivastava et al 2012; Regh et al 2014; Srivastava et al 2015; Worou et al 2015), the SARRA-H crop model (Sultan et al 2005; Baron et al 2005; Sultan et al 2013; Guan et al 2014; Sultan et al 2014), the Agricultural Production Systems Simulator (APSIM) (Akponikpe 2008; Tidjani and Akponikpè 2012; Tachie-Obeng et al 2013; Guan et al 2014; Sultan et al 2014; Mbungu et al 2015; Kisaka et al 2015), as well as the WOrld FOod Studies (WOFOST) crop model (Kassie et al 2014; Kassie et al 2015). The Decision Support System for Agrotechnology Transfer crop model suite (DSSAT-CSM) was also applied at field scale (Salack 2006b; Singels et al 2013; Kassie et al 2014). Recently large-scale crop models were developed and they are applied to allow spatial assessment of vulnerability at regional scale. Examples of those large-scale crop models applied in sub-Saharan Africa include the dynamical global vegetation model (DGVM) incorporating croplands called Lund-Potsdam-Jena managed Land (LPJmL) model (Waha 2012; Waha et al 2013a; Waha et al 2013b; Müller et al 2014), the DGVM named Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) (Bodin et al 2014; Blanc and Sultan 2015), the ORCHIDEE-mil that is also an agro-DGVM developed specially for tropical regions (Berg et al 2011; Berg et al 2013), the global crop model named Predicting Ecosystem Goods And Services Using Scenarios (PEGASUS) (Deryng et al 2011; Deryng et al 2014), the Decision Support System for Agrotechnology Transfer crop model suite (DSSAT-CSM) that operates also at large scale and incorporates many crop models among which the Crop Environment Resource Synthesis (CERES) and generic CROP GROwth model (CROPGRO) crop model families (Ahossane et al 2013; Lawin et al 2013; Somé et al 2013; Ahmed et al 2015; Tesfaye et al 2015), the GIS-based EPIC (GEPIC) model that connects the EPIC model to GIS through data exchange (Wu et al 2008; Liu et al 2008; Folberth et al 2012; Liu et al 2013; Folberth et al 2013; Folberth et al 2014), the GEPIC-V-R model developed for regional crop drought risk assessment based on the GEPIC model combined with scripts for hazard, vulnerability and risk written in VBA and MATLAB (Yin et al 2014), and the General Large Area Model for annual crops (GLAM) (Nicklin et al 2011; Garcia-Carreras et al 2013; Waongo et al 2014a; Waongo et al 2014b; Challinor et al 2015; Matthew et al 2015). According to Yin et al (2014) the large-scale crop models should: (1) allow flexibility for the simulation of different crops under various climatic conditions, (2) simulate yield as well as water stress, (3) require minimum data, and (4) be based on in-depth research in spatialisation. But in these models an accurate estimation of planting dates, which is quite important for a reliable simulation of plant growth, still gives rise to concern because it is often estimated on the basis of climate data only by optimizing those dates against temperature and water demand, regardless of farmers' preferences and other environmental factors like the water holding capacity of the soils (Folberth et al 2012; Waha et al 2013a).

Contrary to the empirical crop models, considerable advantages of the mechanistic crop models are the fact that they account for the response of physiological processes of crop growth and development to environmental and management variables including weather and climate, soil, nutrients and crop management (Tubiello and Ewert 2002; Roudier et al 2011; Bassu et al 2014), with possibility to investigate complex and non-linear interacting factors as well as causal relationships (Tubiello and Ewert 2002; Moore et al 2011; Bassu et al 2014). These models assume that the processes occurring in plants can be satisfactorily represented and the parameters well determined (Landau et al 2000). In these models the crop growth is simulated stage by stage, and the timing and duration of the intra-seasonal climatological variations at each stage can be modelled in a manner consistent with the real agronomic processes (Hertel and Rosch 2010; Ward et al 2014). Compared to the statistical crop models the mechanistic crop models are data intensive. Input data of the process-based crop models are in general the daily climate and weather data, the soil physical properties and initial conditions (soil water soil organic matter and soil nitrogen) as well as the crop and soil management information (Palosuo et al 2011). According to Ward et al (2014) the mechanistic crop models incorporate spatially explicit climate conditions and this makes the yield responses also spatially explicit. But the recording of all the input data are subjected to measurement errors which may introduce some biases in the crop model simulations (van Oijen and Ewert 1999; Palosuo et al 2011; Waha et al 2015).

In the mechanistic models numerous parameters are to be calibrated (Roudier et al 2011). The parameter values needed for the calibration of the mechanistic crop models are either taken from default values in the models, from the literature (empirical data source) or from previous studies that used the selected model (Palosuo et al 2011; Daccache et al 2014). Many scholars also preferred conducting agronomic field experiments to collect site-specific values for calibration and validation (Daccache et al 2014). Folberth et al (2012) indicated that some large-scale crop models are often poorly adjusted to regional conditions and thus may return unreliable results. Before relying on any mechanistic crop model it is paramount to ensure that the selected crop model can satisfactory reproduces the mean and variability from observations. Therefore the crop models are further validated against independent observed data from either field experiments or historical yield data (Daccache et al 2014). In the experimental field conditions many factors are controlled so that the recorded yields are higher than those actually obtained in the farming systems. Therefore the impacts of climate change on the productivity in farmers' fields may be underestimated in case the crop models are validated against data from experimental fields (Parry and Parry 1995). In general the existing mechanistic crop models differ in the input information required, the parameterisation protocols depending upon the objectives and purposes of the models, and methods used to represent the response of crop growth, development and yield processes to the interaction of environmental and management factors (Bassu et al 2014). The mechanistic crop models are not based on the same physiological approach and do not incorporate the same level of details. These differences in parameterisations and representation of processes in the crop models lead to different simulated responses to climate change, thus adding crop model uncertainties to overall climate change impact projections (Roudier et al 2011; Bassu et al 2014). Bassu et al (2014) documented for twenty-three (23) process-based maize crop models often used in impact studies the differences in the procedures used to simulate the major processes governing plant growth and development. According to van Oijen and Ewert (1999) and Walker et al (2003) three major sources of simulation uncertainties arise from crop models. These are: (i) uncertainties related to input data, (ii) parameterisation of crop phenology and other crop cultivars specific parameters, and (iii) model structure (level of simplification of the major processes represented). In addition to those three sources of crop model uncertainty, Palosuo et al (2011) identified human-errors as related to the communication and interpretation of data and model results. They showed that some terms (e.g. rooting depth) are interpreted differently by model users and this adds an additional source of variation in the crop simulation.

Bassu et al (2014) stated that many mechanistic crop models may be equally good at simulating crop yields under past and current climate conditions but respond differently under future climate conditions. A study examining maize crop response to heat and drought stress display contrasting results using seven crop models (Eitzinger et al 2013). Comparing the performance of eight mechanistic crop models (e.g. APES, CROPSYST, DAISY, DSSAT, FASSET, HERMES, STICS and WOFOST) at simulating winter wheat across Europe, Palosuo et al (2011) reported that none of these models perfectly reproduce the spatial and temporal variations of historical yields. Therefore these models cannot be unambiguously declared robust and accurate for crop yield projections with minimum calibration whatever the environmental conditions (Palosuo et al 2011). As it is not possible to validate the physiological crop responses in future climate conditions a thorough assessment of the uncertainties associated with the crop models in various climate conditions is required (Tao et al 2009a; Tao et al 2009b; Rötter et al

2011; Asseng et al 2013; Bassu et al 2014). Many scholars already suggested to take into account both crop model uncertainties and climate model uncertainties to derive sound conclusions on future climate change impact on crop yields (Palosuo et al 2011; Ceglar and Kajfež-Bogataj 2012; Gosling 2013; Rötter 2014; Bassu et al 2014; Challinor et al 2014). Whenever possible robust crop yield estimations (multi-model ensemble) based on multiple crop models forced with many climate models according to different greenhouse gases emission scenarios should be preferred to come up with ensemble projections relatively free of both climate model and crop model dependences (Tao et al 2009a; Tao et al 2009b; Rötter et al 2011; Palosuo et al 2011; Knox et al 2012; Bassu et al 2014; Burke et al 2015). Climate change is also projected to alter the distribution and local severity of crop pathogens and diseases, with some fungal and viral diseases decreasing and other increasing (Garrett et al 2009; Beebe et al 2011), while the emergence of previously unknown pathogens is also plausible (Beebe et al 2011). In addition, cropping patterns that are currently relatively free of insect pests may experience pest build-ups in case higher temperatures and prolonged drought periods favour their year-round survival (Beebe et al 2011; Chakraborty and Newton 2011). But state-of-the-art mechanistic crop models still do not always include the complex effects of changing climate patterns on the spatial distribution and severity of insect pests, crop pathogens and diseases, which may further alter crop development and yields (Ju et al 2013). Another important source of uncertainty of the mechanistic crop models is related to the implementation of plant responses to increasing atmospheric CO_2 concentrations (Tubiello and Ewert 2002; Roudier et al 2011; Asseng et al 2013; Bassu et al 2014). In their comparison of 23 mechanistic crop models Bassu et al (2014) revealed that only 15 models accounted for the CO_2 fertilisation effects, and in those models the CO_2 fertilisation scheme is not identically represented. In fact, to date sound evidence on whether the crop responses to rising atmospheric CO_2 concentrations as implemented in some crop models is consistent and accurate is still lacking. Due to the importance of CO_2 for the photosynthesis activities in crop plants, failure to accurately account for the atmospheric CO_2 fertilization effect largely increases the uncertainty in climate change induced future crop yield changes (Tubiello and Ewert 2002; Asseng et al 2013; Bassu et al 2014).

3 STUDY AREA

This chapter describes the Republic of Benin. Geographical localisation, biophysical and socio-economic characteristics are used herein to depict the environment of Benin.

3.1 Localisation and relief

The Republic of Benin is a country in West Africa, along the Guinean coast. Benin is bordered by Niger to the north (190 km made up of Mékrou and Niger rivers), Burkina Faso to the north-west (220 km of Pendjari river), Nigeria to the east (750 km among which 290 km is formed by the Okpara river), Togo to the west (620 km among which 100 km is formed by the Mono river) and the Gulf of Guinea/Atlantic Ocean to the south (Figure 3.1).

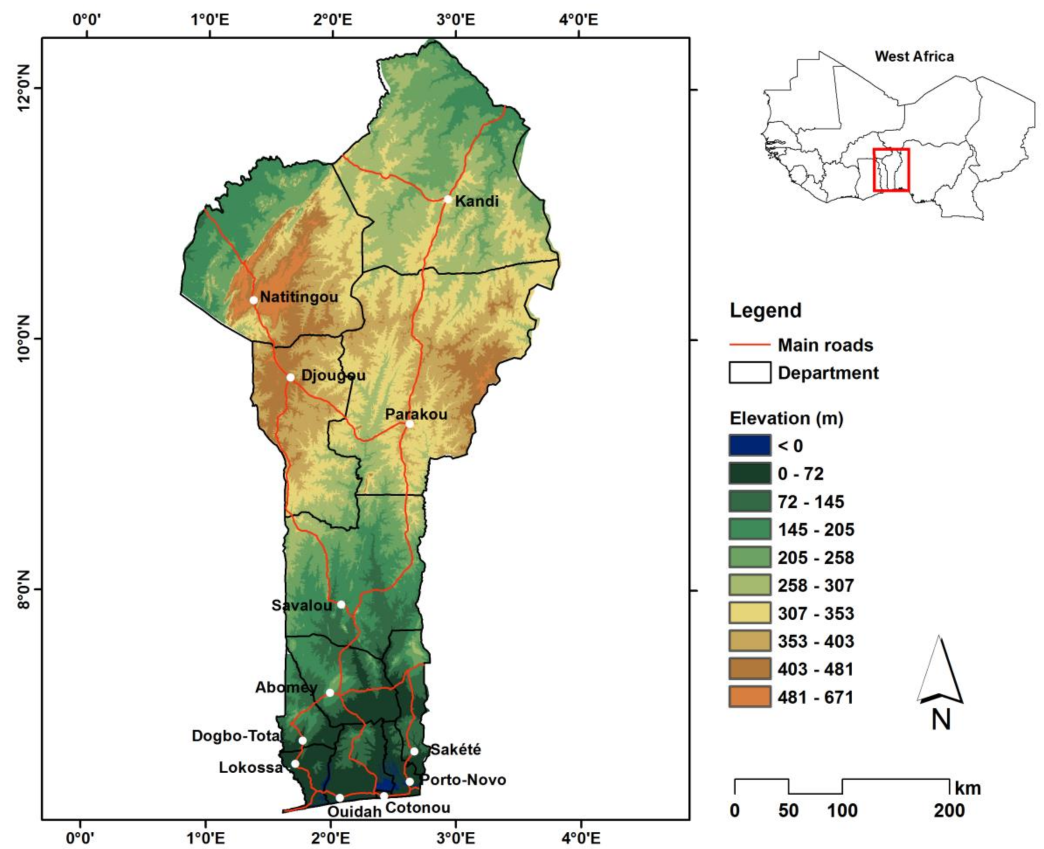


Figure 3.1: Digital elevation map of the Republic of Benin showing the localisation of the country, the topography, and the main administrative divisions.

Data source: Shuttle Radar Topographic Mission (SRTM) of 90 m resolution from the Earth Resource Observation and Science Center /United States Geological Survey.

Benin extends from the Niger River in the north to the Atlantic Ocean in the south over a distance of 714 km. In the south the coastline measures 125 km. The country stretches over about 325 km at its widest point around 11° North latitude, between Tanguiéta (west) and

Ségbana (east). Benin's area is about 112622 km^2; its latitude ranges from 6°20' North to 12°25' North and longitude from 0°45' East to 3°47' East (Tanguiéta - Ségbana) and from 1°35' East to 2°47' East (Lokossa – Sakété). The country is divided into 12 departments and 77 districts (i.e. municipalities or communes). Overall the Republic of Benin is a flat country with an average altitude of 200 m above sea level. The altitude ranges from -51 – 65 m along the Atlantic coast to 658 m (mount Sokbaro) in the north-western part of the country (Adam and Boko 1993; Mama 2013). This has given rise to four major landforms namely the coastal plain, the plateaus, the crystalline peneplain and the Atakora mountain (Adam and Boko 1993).

3.2 Geomorphology and hydrographic network

3.2.1 Geomorpholgy

The Republic of Benin can be divided into four areas from south to north (Figure 3.2). The low-lying, sandy, coastal plain is found in the most southern part of the country and extends 2 to 5 km from the Atlantic coast. Its highest elevation is about 10 m and it is marshy and dotted with some swampy inland-valleys, lakes and lagoons communicating with the ocean.

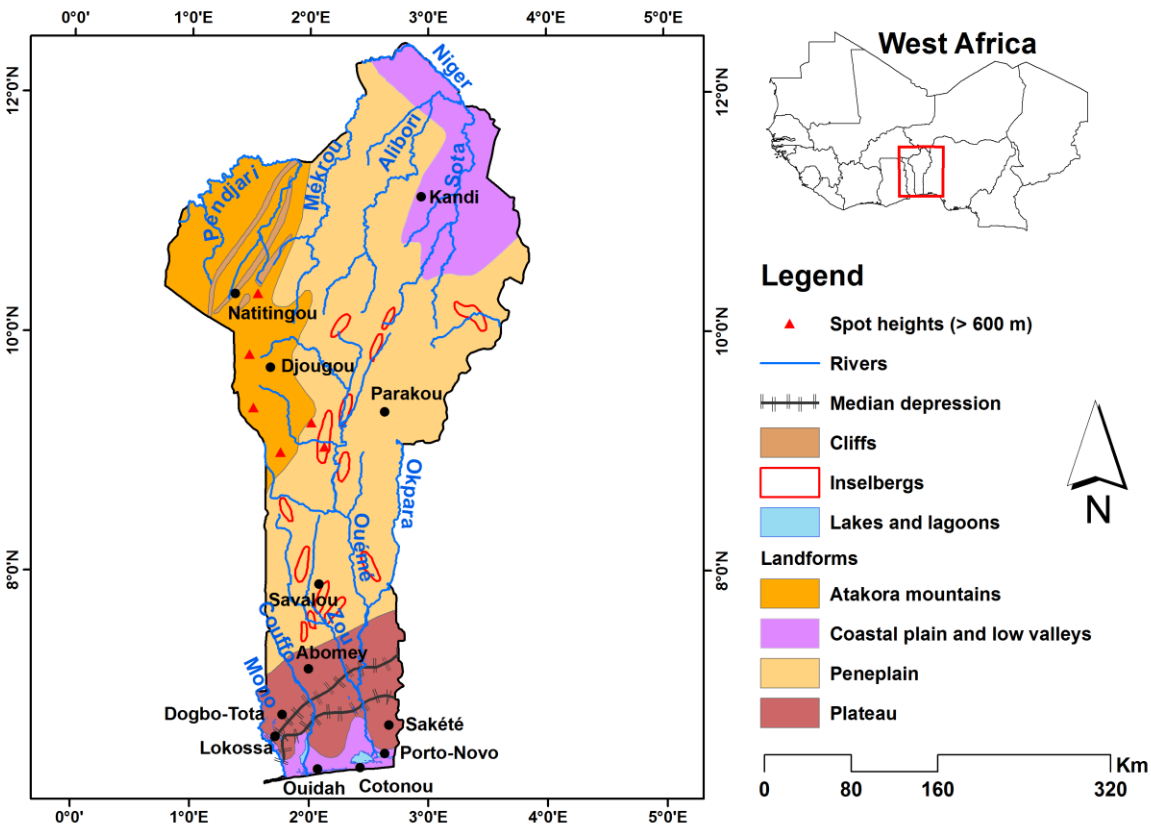


Figure 3.2: Landforms and rivers' network of the Republic of Benin.
Data source: Adapted from Adam and Boko (1993).

Just above this coastal plain, the so-called plateaus of "terre de barre" are found. With an elevation between 20 and 200 m, those plateaus are slightly tilted towards the south and divided into two groups by a median depression of 130 km length oriented from West to East. This depression is called either Lama depression, Tchi depression, Issaba depression or Ko depression according to the localities it crosses. At the south of this depression three plateaus (Plateaus of Comè, Allada and Porto-Novo – Pobè) with an average height ranging from 40 to 100 m characterise the relief while at the north four Plateaus (plateaus of Aplahouè, Abomey, Zagnanado and Kétou) with an average altitude between 80 and 150 m dominate. Above these Plateaus is found the crystalline peneplain. With an average altitude between 200 and 300 m, the crystalline peneplain constitutes the major part of the country. This peneplain is formed by very old granito-gneissic rocks and extends up to Kandi in the north-eastern part of the country. On this peneplain some scattered inselbergs with bare bedrocks occur as inclusions. Above this crystalline peneplain the terrain is a sandstone plateau. This sandstone plateau is found in the north and north-east of Benin and contains many hillocks with small slopes. Finally in the north-western part is found the Atakora mountain (400-658 m height). Oriented NE-SW between the Republics of Benin and Togo, it stands as the highest relief in Benin and extends over 5 km to 45 km (Adam and Boko 1993; Faure and Volkoff 1998).

3.2.2 Hydrology

Benin has many hydrographical networks including 3048 km of watercourses and 333 km^2 of water bodies (lakes and lagoons) located in the southern part of the country. Three basins feed this network: the Niger basin, the Pendjari basin and the Coastal basin (Le Barbé et al 1993).

The Niger basin is derived from the Niger river, one of the largest in Africa (4206 km), and serves as a 120 km border between Benin and Niger. The Niger basin is made up of three rivers: Mékrou (410 km), Alibori (338 km) and Sota (250 km). The Pendjari basin in the west (380 km) takes its source from the Atacora mountain range in Benin, flows towards the northwest, moving towards the southwest into the Republic of Togo where it is known as Oti, before flowing into the Volta river in Ghana. With the exception of the Niger river, all these rivers have the same tropical tide, rising during the rainy season (July–October) and ebbing towards the end of April. The Coastal basin is made up of three rivers known as: Ouémé, Couffo and Mono. The Ouémé river is the largest in the country (510 km), and is the outlet of two major tributaries: Okpara (200 km) to the left bank and Zou (150 km) to the right bank. It is subject to the influence of the sudanian and subequatorial climates, but has a rather tropical tide. The subequatorial influence is weak and exists only in one small area towards the mouth of the river. It uses the lake Nokoué and the Porto-Novo lagoon as conduits in its path towards the sea. Couffo is a small coastal river of 190 km that takes its source from the Djami mountain range in Togo. It draws water and alluvia from the lake Ahémé. Finally, more to the west, the Mono River (500 km) serves as the border between the Republics of Benin and Togo on the last 100 km of its course. It takes its source from the Alédjo mountain range in Togo, and falls into the Grand-Popo lagoon, which it uses as a conduit into the sea through the so-called Avlo pass. The major water bodies in Benin are: (i) lake Nokoué (150 km^2); (ii) lake Ahémé (78 km^2); (iii) lake Toho (15 km^2); (iv) Ouidah lagoon (40 km^2); (v) Porto-Novo lagoon (35 km^2); and (vi) Grand-Popo lagoon (15 km^2) (Adam and Boko 1993; Le Barbé et al 1993).

3.3 Soil and geology

Soil is a basic resource for food production (Igué et al 2014). In the Republic of Benin soils vary significantly as much in nature as in fertility and geographical distribution. According to the soil classification made by the French soil scientists (CPCS 1967), five major soil types can be identified in Benin. These are: (1) tropical ferruginous soils, (2) ferralitic soils, (3) hydromorphic soils, (4) vertic green soils, and (5) rough and undeveloped mineral soils. The tropical ferruginous soils with many variations are developed on granito-gneissic formations of central and northern Benin, and on the schists in the north-western part of the country. The tropical ferruginous soils occupy approximately 70% of the country's area. The ferralitic soils are formed on the continental terminal and cretaceous sandstone. These ferralitic soils cover approximately 7 to 10% of the total surface area of the country. The hydromorphic soils cover between 5 and 8% of the country and can be found in the valleys, basins and alluvial plains. The vertic green soils cover approximately 5% of the land and are usually found in the median dip (i.e. between the northern and southern parts of the country). Finally, the rough and undeveloped mineral soils occupy between 5 and 7% of the land. They are usually found in coastal areas and rocky outcrops of central and northern Benin (NAP/DC 1998; Aregheore 2009). Figure 3.3 shows the different soil types in Benin.

In geological terms the Republic of Benin is located mostly on the Precambrian crystalline rocks usually known as the "basement complex". Indeed it is the widely spread geological unit in Benin. The crystalline basement of Benin is surrounded by three sedimentary basins. These are: (1) the coastal basin (meso-Cenozoique) in the south, (2) the basin of Kandi in the north-eastern (Palaeozic), and (3) the precambrian voltaic basin in the north-western part of Benin.

Southern Benin lies on the coastal sedimentary basin that extends from Togo to Nigeria. Immediately above this sedimentary basin is located the precambrian crystalline rocks usually known as the "basement complex" in Benin and located immediately to the north of the continental terminal area.

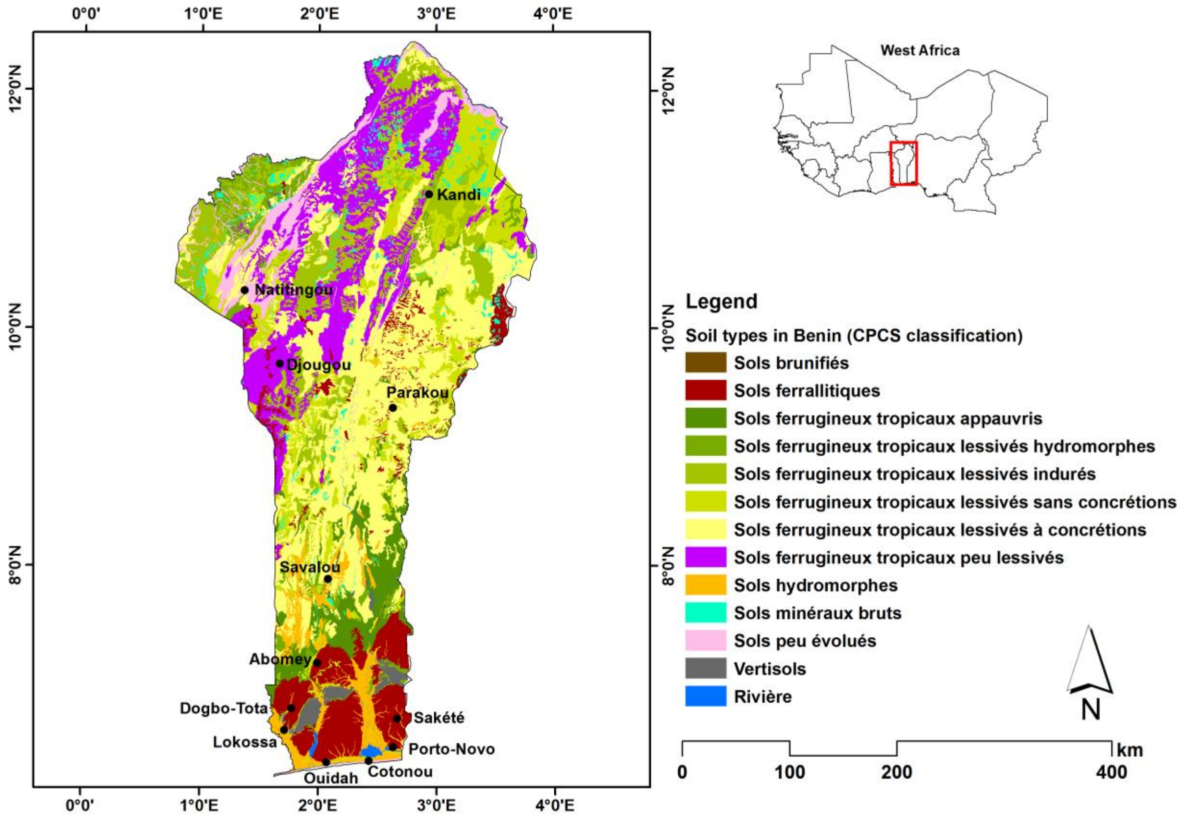


Figure 3.3: Soil map of the Republic of Benin
Data source: ORSTOM pedological exploration map of the Republic of Benin, scale : 1/200000.

3.4 Climate, land cover/land uses and agro-ecological zones

Benin has a tropical climate (hot and humid) with rainy and dry seasons. The northern part of Benin is characterised by one rainy season with a unimodal distribution (peak in August). The number of rainy months varies with the latitude. Northern Benin belongs then to the sudanian climatic zone (Aubréville 1949). The average annual rainfall varies between 950 mm and 1100 mm. The wet season starts from late mid-June to late October while November to April/May represent the dry season. The mean annual temperature is around 27°C with an average relative humidity of 50% per year. But the extremes of temperature reach 39°C in April for the maximun and 16°C in December for the minimum (Vissin 2007).

In the central part of the country the rainy season is also actually uni-modal and lasts from April to October. The mean annual temperature is around 26°C. The temperature fluctuates between 28°C and 24°C. This shows that central Benin belongs to the sudano-guinean zone (Aubréville 1949; White 1983).

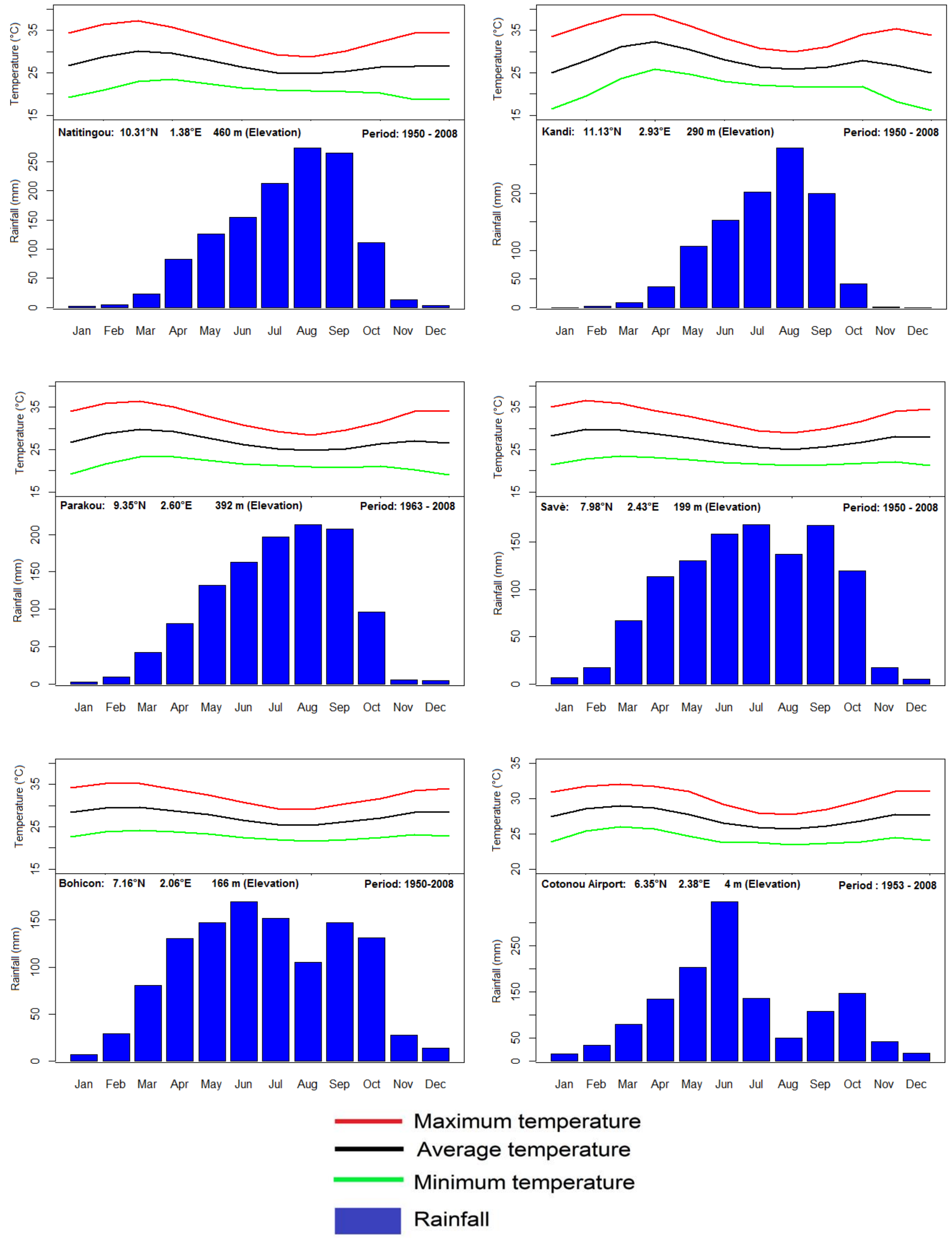


Figure 3.4: Rainfall and temperature patterns in the Republic of Benin.
Data source: ASECNA-Benin

In the south of Benin, the rainfall distribution is bi-modal with two rainy seasons separated by a short dry season in August, and a long dry season from November to March. This leads to a subequatorial climate with four seasons (Adam and Boko 1993). The first rainy season lasts from April to July while the second rainy season covers September and October. The mean annual temperature varies between 23°C and 32°C. Figure 3.4 summarizes the monthly variations of rainfall and near-surface air temperature in Benin during the time period from 1950 to 2008. Nowadays, Benin and West Africa in general are characterised by a great irregularity of annual rainfall from one year to another and within each year.

By its geographical location, Benin is nested into the inter-tropical zone. Its climatic condition is therefore typical of the West African climate, which alternates between the south-west monsoon flow (from the equatorial Atlantic) during the cool and wet season, and the high thermal amplitude north-easterly Harmattan winds that blow during the dry season (from the Sahara) (Aregheore 2009). From the classical picture of the West African Monsoon circulation depicted in many references, over West Africa these two sets of powerful winds (Monsoon and Harmattan) recede alternately towards north into West Africa in the boreal summer and south into southern Africa in the austral summer, thus traversing twice the equatorial regions (Nicholson 2001). Their idealised point of convergence, called in the literature either Inter-Tropical Convergence Zone (ITCZ), rain band or tropical rainbelt, is the central point of all precipitation that causes atmospheric disruptions. Rain production is assumed to emanate from local thermal instability in warm and humid air, with ascent facilitated by the low-level wind convergence within the zone (Nicholson 2013). But in recent years this classical picture of the West African Monsoon (WAM) circulation has raised some controversies. In the revised view of the West African Monsoon, the importance of the ITCZ is reduced and many jet streams and shear zones are included as well as the African Easterly Waves (AEWs), the Saharan Heat Low, and Mesoscale Convective Systems (Nicholson 2009; Nicholson 2013). Indeed, the West African Monsoon (WAM) system is now considered as a system consisting of many atmospheric features interacting in a complex way and controlling the location and latitudinal excursion of the tropical rainbelt (Nicholson 2001) over West Africa. These atmospheric features include : (1) the low-level monsoon flow, (2) the mid-tropospheric African Easterly Jet (AEJ) appearing over West Africa during the boreal summer, and (3) the synoptic disturbances along the African Easterly Waves (AEWs) and the upper level Tropical Easterly Jet (TEJ) (Browne and Sylla 2012). Due to thermodynamic contrasts between the Sahara and the equatorial Atlantic ocean a seasonal wind shift is produced. This gives rise to a south-westerly flow between the equatorial Atlantic cold tongue and the Saharan heat low and brings moisture into the continent. During the boreal summer an intense heat low called either Saharan Heat Low or West African Heat Low evolves over the western Sahara and controls the penetration of the monsoon into the continent. Thus the cyclonic flow around this Saharan Heat Low includes the south-westerly “monsoon” flow to the south and the north-easterly Harmattan to the west of its core (Nicholson 2013). Detailed descriptions on both the classical and revised pictures can be found in Nicholson (2009).

Like her neighbouring countries (Nigeria, Ghana and Côte d’Ivoire), Benin is not a forest country. Savannah is the dominant land cover class of Benin’s landscape (69% in 1972-1973 and 50.34% in 2006) (Mama 2013). As already shown by the reduction of the savannah cover between 1972-1973 and 2006 the landscape of Benin is undergoing degradation. The forests that looked like big patches in the landscape in 1972-1973 are severely fragmented and appear as scattered small patches in 2006. In fact in 2006 the forests still cover just 16.23% of the territory whereas the cover in 1972-1973 was 22.02%. These reductions of the natural vegetation covers are mainly due to cropland expansion. Between 1972-1973 and 2006 the cropland areas increase from 7.70% of the country area to 28.30% (Mama 2013). Figure 3.5 displays the spatial configuration of the landscape transformation that occurred between 1972-1973 and 2006.

About 65% of the whole country is covered by bushy vegetation. PAGE (Pilot Analysis of Global Ecosystems) calculations based on Global Land Cover Characteristics Database (GLCCD 1998) revealed that the Republic of Benin is the country with the highest coverage of grassland in sub-Saharan Africa (Aregheore 2009). Table 3.1 summarises the types of natural vegetation found in Benin, depending on the various climatic conditions. In addition, based on the climate, vegetation types and the different socio-economic activities related to agriculture, the Republic of Benin is divided into eight Agro-Ecological Zones (AEZs) (Figure 3.6). Table 3.2 presents the description of these AEZs.

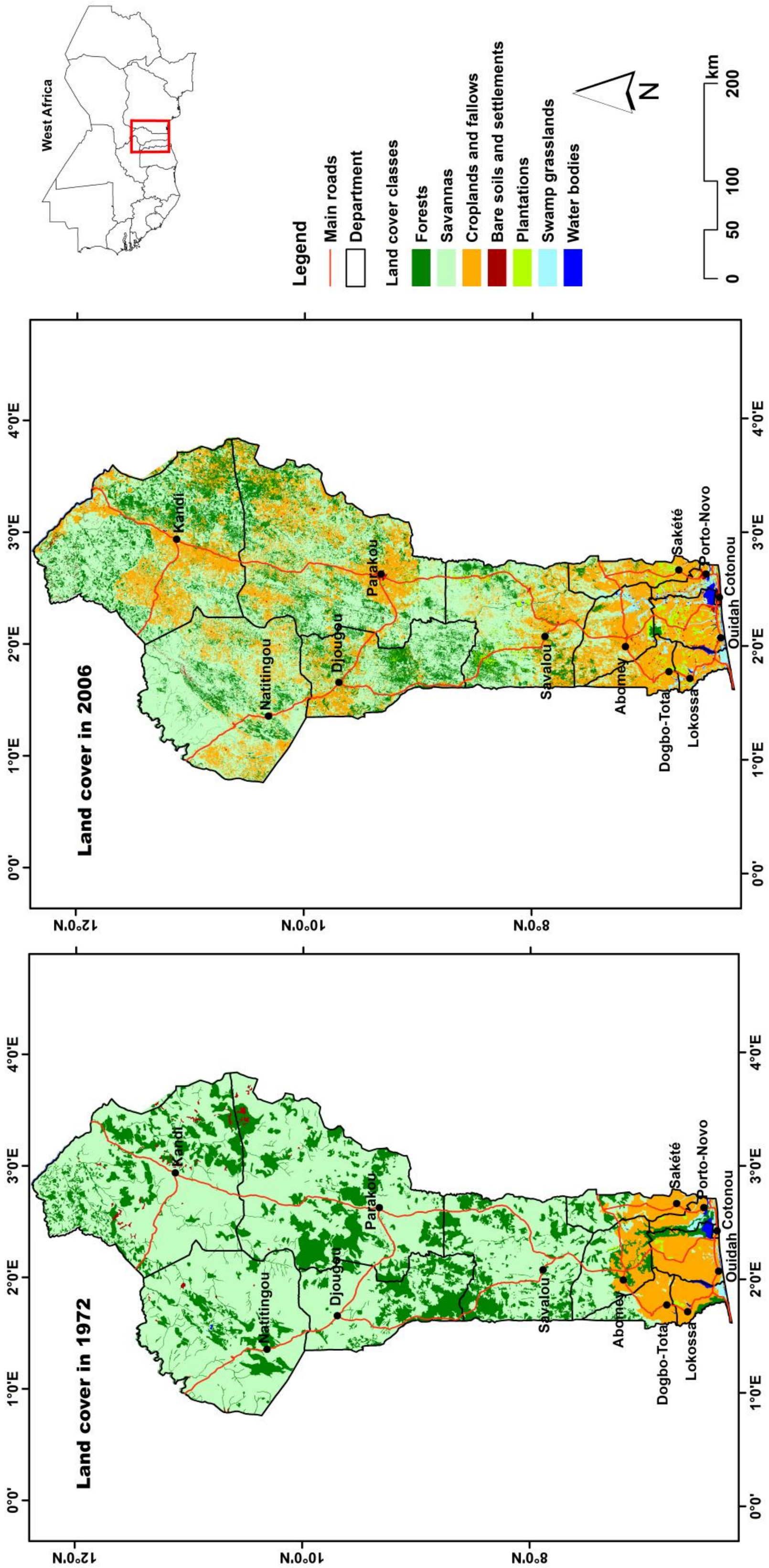


Figure 3.5: Land cover changes in Benin between 1972/73 and 2006 from Landsat imageries for 1972, 1973, 2005 and 2006.

Data sources: Data from the "Projet pilote sur la surveillance continue de la couverture forestière tropicale" (RPB/PNUE/FAO 1978), and processing of 7 scenes of Landsat 7 Enhanced Thematic Mapper Plus (ETM+) of 2005/2006 over Benin by Mama (2013).

Table 3.1: Vegetation types in the Republic of Benin

Location	Climate type	Vegetation type	Dominant species
Northern Benin (10°N - 12°30'N)	Sudano-sahelian climate	Shrubby and wooded savannahs	*Lophira lanceolata, Combretum spp, Balanites aegyptiaca,* etc.
		Open forests	*Anogeissus leiocarpa Isoberlinia doka*, etc.
		Riparian forests	*Khaya senegalensis, Diospyros spp., Mimosa pigra, Daniellia oliveri*, etc.
Central Benin (8°N - 9°30'N)	Guinea-Sudan climate	Dry thick forests	*Isoberlinia doka, enkeri, Khaya senegalensis, Erythophleum guineense, etc.*
		Open forests and savannahs	*Anogeissus leiocarpa, Guieria senegalensis, Boscia salicifolia, Albizia chevaileri*
		Riparian forests	*Ceiba pentandra, Milicia excelsa, Khaya senegalensis, Diospyros mespiliformis and Vitex doniana*
Southern Benin (6°20'N - 7°55'N)	Subequatorial climate	*Ipomoea* lawn	*Remirea maritima, Ipomoea sarifolia*
		Open forests	*Lophira lanceolata, Carissa edulis, Byrsocarpus coccineus*
		Marshy formation	*Cola grandiflora, Ceiba pentandra, Raphia hookeri, Raphia vinifera*,etc.
		Mangrove formation	*Rhizophora racemosa, Avicennia germinans, Dalbergia ecastaphyllum*
		Plantations	*Elaeis guineensis, Tectona grandis*

Source: Aregheore (2009)

Table 3.2: Description of the agro-ecological zones (AEZ) in Benin

AEZ	Area (km^2)	Annual Rainfall (mm)	Climate type	Soil type	Natural vegetation	Main crops
AEZ 1	9057	600–800	Soudano-Sahelian 1 rainy season and 1 dry season	Tropical ferruginous	Shrubby savannah	Cotton, maize, millet, sorghum, rice, potato, onion
AEZ 2	20930	600–800	Soudano-Sahelian 1 rainy season and 1dry season	Tropical ferruginous	Shrubby savannah	Cotton, maize, sorghum, yams
AEZ 3	23442	900–1300	Sudano-Guinean 1 rainy season and 1 dry season	Tropical ferruginous	Woody savannah	Sorghum, cotton, maize, yams
AEZ 4	16936	900–1200	Sudanian 1 rainy season and 1 dry season	Tropical ferruginous	Treed savannah	Sorghum, cotton, maize, yams, cowpea, millet
AEZ 5	32163	1000–1200	Transitional (no clear distinction between the two rainy seasons)	Tropical ferruginous	Woody savannah	Maize, cashew, cassava, cotton, groundnut, yam
AEZ 6	6391	1000–1400	Subequatorial 2 rainy seasons and 2 dry seasons	Ferralitic	Relics of forest	Maize, cassava, cowpea, oil palm, vegetables
AEZ7	3280	1000–1400	Subequatorial 2 rainy seasons and 2 dry seasons	Hydromorphic	Marshy formation	Maize, cassava, cowpea (in rotation), vegetables
AEZ 8	2564	1000–1400	Subequatorial 2 rainy seasons and 2 dry seasons	Vertic green or vertisol	Relics of forests	Maize, cassava, cowpea (in association), vegetables

Sources: National adaptation Programmes of Actions for Benin (NAPA-Benin) (MEPN 2008) and Aregheore (2009)

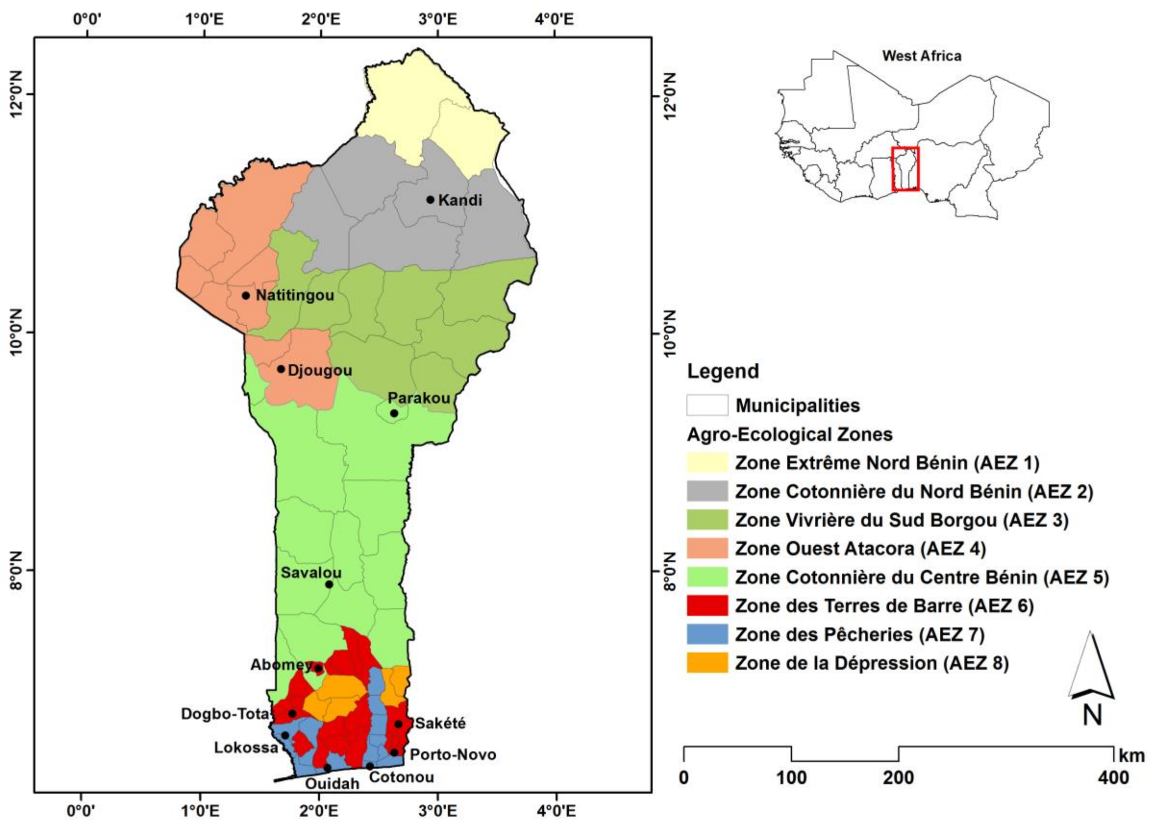


Figure 3.6: Map of the agro-ecological zones of Benin

3.5 Population and economic activities

The Republic of Benin had a resident population of about 10 million in 2013 with growth rates of 2.82% between 1979 and 1992, 3.25% between 1992 and 2002, and 3.51 % between 2002 and 2013 (INSAE 2013). This population is dominantly rural and composed of 42 ethnic groups. The four largest ethnic groups constitute 54% of the population and are made up of the Fon, the Adja, the Bariba and the Yoruba. The 42 ethnic groups in Benin can be divided into five broad cluster groups that are: (1) Voltaic, (2) Sudanese, (3) Fulani, (4) Ewe and (5) Yoruba (Aregheore 2009). Yoruba are found in the south-east (migrated from Nigeria during the twelfth century); Dendi in the central-North area (came from Mali during the sixteenth century); Bariba and Fulbe (Peulh) in the north-east; Betammaribe and Somba in the Atacora region; Fon in the area around Abomey in the South - Central and Mina, Xueda, and Aja (who came from Togo) on the coast. Sub-regional migrations brought to Benin other African nationals mainly from Nigeria, Togo and Mali. In addition, many Lebanese and Indians have settled in Benin and are involved in trade and commerce. The foreign community includes also the personnel of the European embassies, foreign aid missions, non-governmental international organizations (NGOs) and various missionary groups (Aregheore 2009).

The economy of Benin remains underdeveloped and dependent on subsistence agriculture, cotton production, and regional trade. The agricultural sector contributes 39% of GDP and employs about 55% of the active population. With the cotton production, the agricultural sector contributes to about 88% of the export earnings and about 15% of the state revenues (CIPB 2007). There is also production of textiles, palm products and cocoa. Maize, cowpeas and beans, rice, groundnuts, cashews, pineapple, cassava, yams and other various tubers are also produced but mainly for home consumption and local market (Igue et al 2000; Aregheore 2009).

As the major cash crop, with a production record of 427000 tonnes during the 2004/2005 crop production year, cotton production is decreasing. The future of cotton currently gives cause for concern in view of: (1) the environmental degradation, (2) the dysfunction in the structure stemming from reforms in the sector, and (3) the fluctuation in global prices that negatively impacts on rural revenues and the country's economy. Crops such as pineapple and cashew nuts have been accorded some recognition since the adoption of the country`s strategic planning for the revival of the agricultural sector in 2007 (CIPB 2007; Aregheore 2009; MAEP 2011). Pineapples are exclusively produced in southern Benin, mainly in the Altantique department (in the districts of Abomey-Calavi, Allada, Zè, Toffo and Tori-Bossito in the AEZ 6) from which comes 95% of the national production of that agricultural commodity (Fassinou Hotegni et al 2010; Adossou 2012). The production from oil palm went from 130000 tonnes in 1994 to nearly 280000 tonnes in 2005. These levels of production are largely inadequate to satisfy national and regional market needs (CIPB 2007; Aregheore 2009).

Food crop production largely consists of grain on nearly 1100000 ha of which 54% are devoted to maize. Production in 2005 was estimated at 841000 tonnes for maize, 207000 tonnes for sorghum and 73000 tonnes for rice. Maize is the most profitable grain but its 2004 production level (going by an average consumption hypothesis) left a staple reserve of only 124830 tonnes against 161840 tonnes in 2005 (CIPB 2007; Aregheore 2009). This is not enough given that it is the base component in the manufacture of children's cereals and poultry feed. Rice has become a strategic crop with growing importance in the national consumption pattern and trade between neighbouring countries (Niger, Nigeria and Togo). Although its level of production is increasing (from 16045 tonnes in 1995 to 73000 tonnes in 2005, and 206943 tonnes in 2013), there are still significant imports (over 450000 tonnes in 2004 and approximately 378000 tonnes in 2005) to complement internal and re-exportation needs (CIPB 2007; Aregheore 2009).

The fishery subsector mobilises about 50000 fishermen and 20000 fisherfolk (most of whom are women). This subsector accounts for about 2% of Benin Gross Domestic Product (GDP). During the time period from 1998 to 2005, the production stagnated around 40000 tonnes/year and the importation of frozen fish increased from 20000 tonnes in 2001 to 45000 tonnes in 2005. Furthermore, the export of shrimps, once a potential source of revenue, fell from 1000 tonnes to less than 700 tonnes in the same period (CIPB 2007). The waterways are not judiciously exploited while aquaculture and fish production are still underdeveloped (CIPB 2007; Aregheore 2009). The livestock subsector accounts for approximately 6% of the GDP and is still characterised by traditional practices of raising stock of cattle, goats, pigs and poultry (CIPB 2007; Aregheore 2009).

The forestry subsector is characterized essentially by a continuous degradation of the forest resources and of the wild fauna as a result of increasing human pressure on the resources. This situation is really alarming because: (1) an important and increasingly fringe of the populace lives under the poverty line and over-exploits the natural resources to survive, and (2) the needs in firewood and timber are increasing due to population growth and to the development of economic activities (CIPB 2007; Aregheore 2009).

4 DATABASE

This Chapter presents the set of climate and agricultural data that were used in this study for predictive purposes. The observational and simulated climate datasets are monthly values and were considered only on a domain extending over 20°W – 40°E and 0° – 40°N. The historical yield data are values per crop production year collected at the district level and aggregated to the whole country. The cropping calendars are used to derive the growing season months.

4.1 Observational climate data

Observational climate data are needed to describe climate patterns, assess the performance of climate models and calibrate impact models in present-day. The data are obtained from either land-based networks of meteorological stations (e.g. HAdGHCND, GPCC, and CRU datasets) or meteorological observation satellites (e.g. TRMM 3B 42 and TAMSAT datasets). Some datasets are also derived from the combination of gauge measurements and satellite products (e.g. operational RFE 2.0, climatological RFE, and GPCP). For regional applications, the station records are spatially interpolated to generate gridded datasets $X(t, s)$ where X stands for the variable of interest (e.g. precipitation, temperature, etc.) whereas t and s stand for the temporal and spatial resolutions respectively.

The gridded precipitation and land surface temperature databases available for studies in Africa are listed in Table 4.1. The different datasets come from various international data centres. Each of these datasets covers different time periods at different spatial and temporal resolutions. The fidelity of all these datasets in representing the real African climate is questionable (Paeth et al 2005). Indeed, uncertainty is inherent in all the observation products, especially in data sparse areas (Sylla et al 2012; Gbobaniyi et al 2014). As pointed out by Pinker et al (2006), the satellite estimates generally overestimate precipitation over semi-arid regions of the African continent. This is certainly due to the fact that algorithms translating measured radiation to effective rainfall amount are still subject to some uncertainties (Paeth et al 2005). Nikulin et al (2012) have compared TRMM data (Tropical Rainfall Measuring Mission) to GPCP data (Global Precipitation Climatology Project, a satellite-gauge combination) (Adler et al 2003) and found that TRMM exhibits significant dry bias up to 50% over some regions in tropical Africa. Many other scholars have also shown that combined satellite-gauge information often outperform the current satellite only products (e.g. Nicholson et al 2003a,b; Dinku et al 2007; Paeth et al 2011b; Parker et al 2011). But these combined products also do not always lead to much added-value when compared to some gauge-datasets like GPCC (Global Precipitation

Climatology Centre), especially in the Western Africa (Nicholson et al 2003a; Nicholson et al 2003b; Ali et al 2005).

Table 4.1: Observational climate datasets available for regional studies in Africa

Datasets	Variables	Spatial coverage	Spatial resolution	Temporal resolution	Temporal coverage
HadGHCND	Tmin & Tmax anomalies	Global	3.75° x 2.5°	daily	1950 – present
CRUTEM	Tmean anomalies	Global	5°	monthly	1851 – present
GISS	Tmean anomalies	Global	2°	monthly	1880 – present
NCDC	Tmean anomalies & Total precipitation	Global	5°	monthly	1880 – present (Tmean anomalies), 1900 – present (PRE)
CPC	Tmean & Total precipitation	Global	0.5°	monthly (Tmean), daily (PRE), 10-day (PRE)	1948 – present (Tmean), 1979 – present (PRE)
UDEL	Tmean & Total precipitation	Global	0.5°	monthly	1900 – 2008
CRU TS	Tmean, Tmax, Tmin, diurnal temperature range, Total precipitation & wet day frequency	Global	0.5°	monthly	1901 – 2013
GPCC first guess	Total precipitation	Global	1° & 2.5°	monthly	Oct. 2003 – present
GPCC monitoring	Total precipitation	Global	1° & 2.5°	monthly	1986 – present
GPCC reanalysis	Total precipitation & anomalies	Global	0.25°, 0.5°, 1° & 2.5°	monthly	1901 – 2010
GPCC gridded climatology	Total precipitation	Global	0.25°, 0.5°, 1° & 2.5°	monthly	1951 – 2000
GPCC – 50 year VASClimO	Total precipitation	Global	0.5°, 1° & 2.5°	monthly	1951 – 2005
CMAP	Rain rate	Global	2.5°	monthly	1979 – 2009
CAMS-OPI	Rain rate	Global	2.5°	monthly	1979 – present
TRMM	Rain rate	50N-S.	0.25°	monthly, daily, 10-day	1997 – present
GPCP 1DD	Rain rate	Global	1°	daily, 10-day	Oct. 1996 – present
GPCP GPI	Rain rate	40N – 40S	1°	daily, 10-day	1996 – present
GPCP	Rain rate	Global	2.5°	monthly	1979 – present
GPCP intermediate products	Rain rate	Global	2.5°	monthly	1979 – present
CMORPH	Rain rate	60N – 60S	0.25°	daily, 10-day	2002 – present
CPC-RFE operational	Rain rate	40S-40N / 20W-55E	0.1°	monthly, daily, 10-day	1995 – present
CPC-RFE climatological	Rain rate	40S-40N / 20W-55E	0.1°	monthly, daily, 10-day	1983 – present

TAMSAT	Total precipitation & anomalies	All Africa land	0.04°	10-day	1982 – present

Source: adapted from Parker et al (2011).

In general, some authors have suggested that the discrepancy between all the datasets might be due to the facts that: (1) they use different gauge analysis products (Huffman et al 2009; Nikulin et al 2012), (2) the number of observations used in these products varies over time and regions (Sylla et al 2012), and (3) different retrieval, merging and interpolation techniques are applied (Sylla et al 2012; Panitz et al 2013). As pointed out by Zhang et al (2012) and Panitz et al (2013) station errors are particularly relevant in areas where almost no gauge data are available (e.g. central Africa) because of their large spatial influence. However, good agreement between GPCC, GPCP, and CRU datasets have generally been reported except in areas like Angola and the Democratic Republic of the Congo where the number of gauge stations is very limited (Zhang et al 2012; Panitz et al 2013; Harris et al 2014a). Gbobaniyi et al (2014) have also confirmed that GPCP and CRU agree well in representing the inter-annual variability in the Sahel with a high correlation coefficient of around 0.96 but reported relatively low correlation (0.63) over the gulf of Guinea. Nevertheless they have all concluded that considering one or the other dataset as reference does not change the conclusion.

In this study, CRU time-series was selected for impact application due to its high spatial resolution, long temporal coverage and large spatial coverage. This dataset has also the advantage of being freely available and consistent over time for the two climatic variables of interested in this study (i.e. total precipitation and mean near-surface air temperature). Herein, the CRU dataset serves as reference for representing the pattern, mean and trend of the present-day climate. The CRU dataset has already been extensively analysed by Brohan et al (2006). It has also been intensively used for different research purposes; for example climate models assessment (Paeth et al 2005; Trenberth et al 2007; Paeth 2011; Jacob et al 2012; Nikulin et al 2012; Kim et al 2013) and human disease transmission (Gaardbo Kuhn et al 2002; Ermert et al 2012). It has also been widely used in crop impact research (Lobell and Field 2007; Tao et al 2008; Deryng et al 2014) and is thus regarded as suitable for this study.

First version of CRU time series (CRU TS 1.0) was developed by New et al (2000) for 1901-1995. The dataset has been updated 8 times. The construction methodology has been improved and many climate variables added to precipitation and mean temperature. Currently, the most recent release (i.e. CRU TS 3.22) (Harris et al 2014a) supercedes all the previous versions and comprises 10 surface climate variables for 1901-2013 time period (Harris et al 2014a). However in this study, CRU TS 3.10 for 1901-2009 was used because it was the most recent at the start of these analyses. CRU TS 3.10 (herein referred to as CRU) is publicly available on the Climatic Research Unit portal (http://www.cru.uea.ac.uk) and the British Atmospheric Data Centre (BADC) portal (badc.nerc.ac.uk/data/cru/) on a regular high spatial resolution (0.5° grid) and represents century-long time series. Indeed it is a monthly time series of various climate variables including precipitation and air temperature developed by the Climatic Research Unit of the University of East Anglia in Norwich, UK (Mitchell and Jones 2005; Harris et al 2014a). The monthly database is built from *in situ* meteorological stations from all around the world and spans the period from 1901 to 2009 at a spatial resolution of 0.5° x 0.5° latitude/longitude over all land masses. Therefore it covers the terrestrial surface including oceanic islands but excluding Antarctica.

The CRU dataset is constructed using the Climate Anomaly Method (CAM) developed by (Peterson et al 1998). Only the stations with at least 75% of non-missing values in each month through the reference period (1961-1990) were included in the gridding operations. Those stations values were used to compute monthly climatology per station provided that they have fallen within the range of 3 times (4 times for precipitation) standard deviation departure from the normal. For the stations that passed the screening, the time series were converted to monthly anomalies relative to their average on the reference period. Depending on the station locations, the anomaly values were further on interpolated to a half degree grid cell resolution through triangulated linear interpolation. First, for each variable a correlation decay distance (CDD) (New et al 2000) was defined to determine the stations to be considered to infill each land grid cell. The monthly anomalies were then passed to the gridding routines only if a least one station falls in a land grid cell within the CDD. In case no station falls in a given land grid cell, the empty cell is given 0 as anomaly value. This yields 0.5° regular gridded anomalies for all global land areas. The gridded anomalies were finally converted to absolute values (construction of the time series) by combining them with the monthly gridded reference climatology (New et al 1999) used in the earlier versions of the CRU TS dataset (cf. Harris et al 2014 for detailed description of the dataset).

Figure 4.1b,c showcase the spatial patterns of the annual climatology of precipitation and air temperature over large part of Africa, as revealed by the CRU dataset. The CRU dataset suffers from highly irregular stations distribution in some African regions (Nikulin et al 2012), especially low populated areas like the Sahara. In fact, in areas of poor in situ measurements, the anomaly interpolation method leads to a relaxation of monthly fields towards the reference climatology, and increases interpolation errors wherever the gauge network is sparse (e.g. over cold, dry, and mountainous regions), especially in tropical regions (New et al 2002). This irregular distribution problem affect mainly precipitation analysis since precipitation is highly localised in West Africa for example (Kim et al 2013). Thus, the CRU dataset may likely contain some unknown errors which may bias the identification of relationships between crop yield and climate in some regions (Lobell 2013; Osborne and Wheeler 2013).

4.2 Simulated climate data

Global and regional climate models are used for paleo-climate simulations as well as present-day climate and possible future climate change assessments and in climate impact modelling and adaptation studies (IPCC 2007; Paeth et al 2008a; Lopez et al 2009; Brown et al 2011; McAfee et al 2011; Harrison et al 2012; Chen et al 2012a; Srivastava et al 2012; Choi and Cha 2012; Brown et al 2012; IPCC 2013; Schmidt et al 2013; Teichmann et al 2013; Oguntunde and Abiodun 2013; Hertel and Lobell 2014; Saito et al 2014; Yang et al 2014). The horizontal resolution of present-day global climate models is still coarse (mostly 300 to 100 km) (Meehl et al 2007; Tian et al 2013). Therefore, most global climate models are not capable of capturing significant subgrid scale features like complex topography and land surface characteristics (Tian et al 2013). They do not correctly resolve synoptic or meso-scale processes and thus they are not fully appropriate for regional climate impacts application. This is evident in environmental modelling fields like hydrology, agronomy, ecology etc., where spatially higher resolved information about the present and possible states of the regional climate system is required to investigate the regional or local impacts of different climate conditions (MacKellar et al 2007; Karmalkar et al 2008; Ashfaq et al 2009; Haensler et al 2011; Karmalkar et al 2011), anticipate impacts of climate change and thus design suitable adaptation responses or mitigation options (Paeth and Diederich 2011; Lobell 2013; Teichmann et al 2013). Considerable efforts have been devoted by the climate modellers' community to bridge the gap between the low resolution climate information from the GCMs and the regional or local climate information needed by practical end-users and decision-makers. Two mainstream approaches exist to downscale GCM simulations to a finer spatial resolution for regional or local analysis. These are (1) statistical downscaling techniques which are based on empirical relationships between some local predictors such as latitude, orography, roughness length, distance from coast etc. and the variables to be interpolated (Mearns et al 1999), and (2) dynamical downscaling which uses regional climate models based on additional physical constraints (Paeth et al 2005; Tian et al

2013). Regional climate models (RCMs) like REMO which operate at relatively higher spatial resolution find their way by dynamically refining within a limited area the large scale information about the atmosphere taken from these global climate models (Paeth et al 2005; Paeth et al 2009; Sanchez-Gomez et al 2009; Mariotti et al 2011; Teichmann et al 2013). Regional climate models are now quite often used and regarded as much powerful way of downscaling GCM simulations because they can better represent the local land surface variables that affect the regional climate and internal climate variations (Wang et al 2004; Tian et al 2013). Additionally, contrary to statistical downscaling, RCMs do not rely on the characteristics and the not-always-none accuracy of past meteorological observations (Paeth et al 2005).

The regional climate model REMO is a hydrostatic limited-area three-dimensional atmospheric circulation model developed at the Max-Planck Institute for Meteorology (Jacob and Podzun 1997; Jacob 2001). The model is originally developed over Europe (home region) (Jacob et al 2012), using the dynamical core of the former operational weather forecast model 'Europa-Modell' of the German Weather Service (DWD) (Majewski 1991) and the physical parameterisations of the global climate model ECHAM-4 (Roeckner et al 1996) adjusted to the scale of REMO. It is thus designed to simulate synoptic-scale atmospheric processes (Jacob 2001; Jacob et al 2001; Jacob et al 2007; Jacob et al 2012). The model can be driven over regions different from the home domain, i.e. with different climate characteristics (Jacob et al 2012). Indeed in the framework of the IMPETUS project in West Africa the REMO RCM has been used in its version 5.7 to perform high resolution climate change simulations (0.5° horizontal resolution) over a domain expanding from 30°W to 60°E and 15°S to 45°N, i.e. 121-lat x 181-long regular grid boxes with the southernmost grid in the first column centred on 29.75°W/14.75°S. The domain over which the simulations are realised thus includes large part of Africa, mandatory domain in the Coordinated Regional Climate Downscaling Experiment (CORDEX). In the model version used, 20 hybrid vertical terrain-levels up to a height of 25 km has been implemented (Paeth et al 2005). As frequently done in regional climate modelling studies, large scale climate information has been transported into the model domain via the lateral atmospheric boundaries as well as the lower oceanic boundaries (Teichmann et al 2013). The boundary conditions may be derived by either reanalysis data for present-day simulations or large-scale GCMs for both present-day and future climate change projections. The model can be nested in various global climate models (GCMs) but during the aforementioned project for future projection the model was run in an uncoupled climate mode with prescribed lateral boundary conditions (LBC) taken from the GCM ECHAM-5/MPI-OM every 6 hours. Sea-surface temperatures (SSTs) at the lower oceanic boundaries have been also derived from the GCM ECHAM-5. For the model evaluation in the twentieth century atmospheric and oceanic forcing were both prescribed by the European Centre for Medium-range Weather Forecast (ECMWF) global reanalyses (ERA 15) (Gibson et al 1997). Application of a model outside its home domain often requires adjustment of the values of some model parameters to fit the reality of the domain in which the model is being applied. Therefore, a mass flux scheme of Tiedtke (1989) which governed the moist convection processes has been adapted to the tropical-subtropical climate of the model domain by changing the lower threshold of cloud thickness for rainfall generation to 1500 m instead of 750 m (prior value for the extra-tropics). Soil processes are computed by a 5-layer one-dimensional soil model that has a vanishing heat flux at 10 m depth. The land surface scheme implemented in the model has followed Hagemann et al (1999) with orography taken from the GTOPO30 dataset and other land surface parameters like vegetation cover, albedo, soil characteristics, roughness length etc., taken from NOAA (National Oceanic and Atmospheric Administration) dataset. Some parameters like vegetation cover, leaf area index (LAI) and surface albedo have followed an idealized seasonal cycle so that change in interannual variability cannot result from change in land surface conditions. A more detailed description of the model design can be found in Jacob et al (2001) and Paeth et al (2005, 2009).

For the REMO simulations used in this study two experiments were considered: the first one with only greenhouse gases (GHGs) forcing, and the second one forces with both GHGs and anthropogenic land use/land cover change (LUCC). To accomplish these experiments, two greenhouse gas emission scenarios from the IPCC Special Report on Emissions Scenarios (SRES) were followed for the twenty-first century. Both the SRES A1B and B1 scenarios (Nakićenović et al 2000) were implemented in the second experiment while the first experiment followed only the SRES A1B. For each type of simulation three ensemble-member runs of the model were performed to account for the uncertainty due to the lack of information on the initial conditions. Present-day simulations were performed for the time period 1960-2000 while the future transient climate projections extend over the time period 2001-2050. For all those simulations present-day and future LBCs were derived directly from the coupled GCM ECHAM-5/MPI-OM outputs which themselves are forced with enhanced greenhouse and sulphate aerosols conditions. For the experiment with LUCC, during the twentieth century constant land cover from 1992/1993 is prescribed. From 2001 to 2050 changing land cover is prescribed according to a business-as-usual land cover change process and the GHG emission scenarios SRES A1B and B1. In fact, Paeth et al (2009) developed a high resolution stochastic land degradation model on the basis of the assumptions for future population growth and urbanisation in Africa according to the United Nations report on world population prospects (UN 2006), and the 1 x 1 km^2 resolution International Geosphere Biosphere Programme (IGBP) land cover classification dataset of the USGS Global Land Cover Characterization (GLCC) (Belward 1996). The outputs of this land use model are further on rescaled to fit the resolution of REMO and transformed to the land surface parameters needed in REMO (e.g. vegetation ratio, forest fraction LAI, roughness length, surface albedo). In this model, all the spatial transformation processes, i.e. extension or reduction of a given land cover class and conversion of a given land cover class into another, are extrapolated until 2050. The overall structure of the spatial transformation processes (e.g. conversion of evergreen forests and savannahs to croplands and settlements, grasslands to bare soils etc.) is fairly realistic and matches the estimates by the United Nations – Food and Agriculture Organisation (UN-FAO) (FAO 2006). However, the model is limited in the way that it does not allow the vegetation cover to react to the simulated climate changes, i.e. the interaction of vegetation-atmosphere has not been fully integrated. These REMO simulations provide valuable information about the regional climate change characteristics in sub-Saharan Africa, which may later be used to conduct regional climate change impact studies (Jacob et al 2012). A detailed description of the developed and implemented land degradation model and all the REMO experiments that generated the REMO outputs used is given in Paeth et al (2009).

Paeth et al (2005) argued in their validation study with atmospheric and oceanic forcing provided by ECMWF reanalyses that REMO RCM performed well. REMO is well suited for climate change simulations over sub-Saharan Africa (Jacob et al 2012). The model has successfully reproduced the major features of the real African climate from annual to seasonal scale. The spatial distribution of rainfall climatology from REMO is very close to that from the CRU dataset (cf. fig. 4.1a,b). As well, the simulated spatial patterns of temperature are quite reasonably comparable to the observed ones (cf. fig. 4.1d,e). However, the model has a wet bias in the southern part of the Congo Basin and a warm bias over eastern Arabian Peninsula (Paeth et al 2005; Paeth et al 2009), regions which are not in the focus area of this study as indicated on Figure 4.1b by a red rectangle. As shown by Fig. 4.1c,f over the West African monsoon region (region denoted by the black dots rectangle on fig.4.1b) REMO exhibit systematic warm bias in some areas compared to CRU data. But it has to be kept in mind that, like all other gridded observational datasets, while compared with some available meteorological stations datasets

CRU data itself does not tell us the utmost truth (Paeth et al 2009). Nonetheless, although available RCMs projections in Africa are still characterised by high uncertainty (Paeth et al 2011b), compared to other RCMs simulations in Africa those simulations with REMO have the great advantage of integrating spatially detailed patterns of future land use changes. In fact, in sub-Saharan Africa the land cover change is now well documented for several decades and the degradation process will certainly continue during the twenty-first century as Africa has the highest population growth and this growth is still uncontrolled (Gaiser et al 2011). Anyway, vegetation is no longer considered as a mere spectator in the functioning of the Earth system.

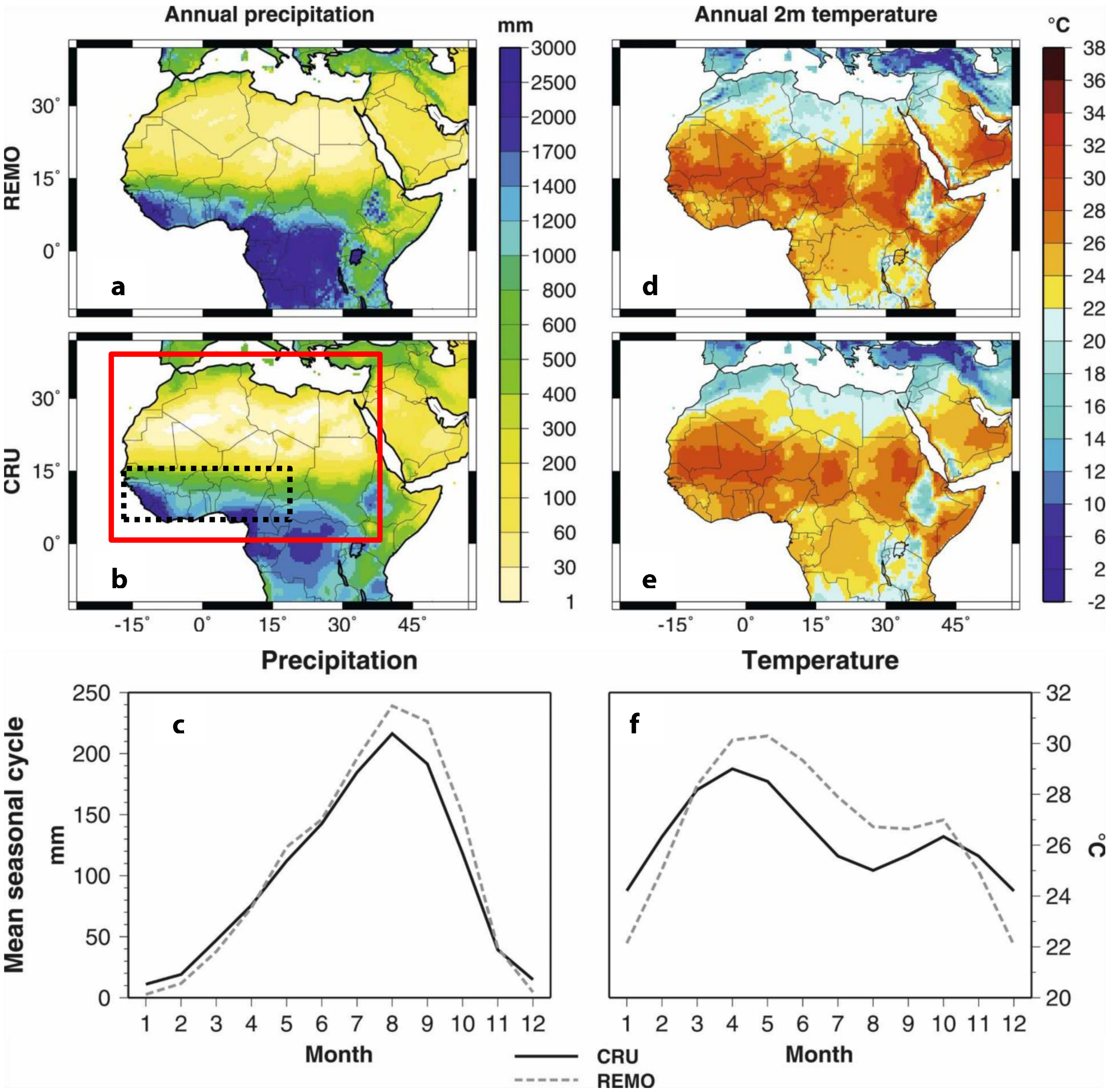


Figure 4.1: Spatial patterns of the 1960-1998 climatology of annual precipitation and air temperature for Africa with associated seasonal distribution over sub-Saharan West Africa, CRU vs. REMO (after Paeth et al (2009), their Figures 3 and 4).

Human land use activities are a force of global significance (Fu 2003; Foley et al 2005; Feddema et al 2005a; Ramankutty et al 2008; Mahmood et al 2010; Dirmeyer et al 2010; Yu et al 2014). After DeFries and Achard (2002) and Houghton (2003), Ramankutty et al (2008) also emphasises that deforestation of the tropical forests for agricultural purposes is responsible for 12–26% of the total release of carbon dioxide (CO_2) to the atmosphere. Recently the scientific consensus says that African terrestrial ecosystems play an important role in global carbon cycle and accordingly in global climate system, and thus in global climate change through its control of energy fluxes over substantial portions of the land surface (Tia 2008; Ciais et al 2009; Bombelli et al 2009; Ago et al 2014). In addition, it is increasingly recognised that land-use changes contribute more CO_2 emissions in Africa than in other regions of the world (Houghton and Hackler 2006; Ago et al 2014), and this can significantly modify regional and global climate (Pielke et al 2002; Ramankutty et al 2008; Mahmood et al 2010; Deng et al 2013; Wang et al 2013; Mahmood et al 2014; Yu et al 2014). Therefore, the climate-vegetation interaction is essential to be included in climate change studies (Tia 2008). Accounting for land use change impacts in a regional climate simulation model is then really a valuable improvement (Feddema et al 2005b).

4.3 Historical crop yields and cropping calendar

Agricultural production strongly contributes to the Gross Domestic Product (GDP) of Benin. The agricultural statistics are collected by each agricultural promotion centre (CARDER) at the district level. The statistical division (SS/DPP) of the ministry of agriculture, livestock and fisheries (MAEP) is the official provider of agricultural statistics in Benin. This division releases after every agricultural year a compendium of the agricultural statistics of the previous year. These statistics are collected per crop at a village-level in each district by the local agricultural promotion centres called Secteurs Communaux de Développement Agricole (SCDA) following a random sampling rate of 1/10 villages among all villages in each district and then 10 farmers' exploitations are also randomly sampled in each of the previous retained villages per district. In each of the selected farmers' exploitations density plots are installed per crop field for data collection. The data from these agricultural census are further extrapolated to the whole district and compiled per department by the regional agricultural promotion centres called Centres Agricoles Régionaux pour le Développement Rural (CARDER). It must be noted that the agricultural promotion centres are distributed accordingly to the administrative subdivision of the country, i.e. one local agricultural promotion centre in each of the 77 districts and one regional agricultural promotion centre for 2 actual departments. The CARDERs quality-check the data and edit their yearly agricultural reports. The data in the agricultural reports are finally aggregated for the whole country by the statistical division at the MAEP. Per crop, production, yield and acreage are provided.

Agricultural data used in this study are taken from the compendiums of agricultural statistics from the MAEP (MDR 2004; MAEP 2010). As also noticed by Camberlin and Diop (1999) for Senegal, the statistics from the official provider sometimes differ from that of the United Nations Food and Agriculture Organization (UN-FAO) (i.e. CountrySTAT and FAOSTAT) or the Central Bank of the West African States (BCEAO) (BCEAO 2006; BCEAO 2013) for the corresponding time period. The MAEP statistics have been preferred because this study was previously interested in only one crop (i.e. pineapple), but the BCEAO dataset contains only production data for six crops excluding pineapple. Although the FAOSTAT dataset (available online at http://faostat3.fao.org/faostat-gateway/go/to/download/Q/QC/E) contains pineapple statistics and is much longer, it has not been chosen because its pineapple statistics lacked inter-annual variations in the years before 1990s as shown in Figure 4.2. In fact, according to the FAOSTAT methodology it is claimed that the pineapple statistics for the period before the 1990s were obtained from unofficial sources such as other national or international agencies or organisations. They have also occasionally used their own imputation methodology to make the coverage of the data collection as complete as possible. Prior to 1995, the agri-food chain for pineapple in Benin was not organised. Consequently, the reliability of any statistics related to pineapple in Benin before 1995 is highly questionable. This study does not claim a much more reliability of the MAEP statistics, but these data can be assumed to reflect official figures since they come from the official provider.

In addition to pineapple, eight other crops namely groundnuts, cotton, yams, maize, rice, sorghum, cowpeas, and cassava have also been considered. For all these crops, available yield data from the MAEP compendiums during the time period 1970 – 2009 were used. Figure 4.3 displays the time series of the annual yield averaged over Benin for the above-mentioned crops. It shows a general inter-annual fluctuation in the yield of all crops but still display slight tendencies to increase over time. Crop yield data have been preferred to production because increase in production might have resulted from an expansion of the area under cultivation. In fact the spatial extent of croplands in West Africa has increased in the past due to shifting cultivation and growing population (Ramankutty 2004). Additionally, Paeth et al (2008) argued that as a result of increasing food demand due to significant population growth, an increase in the cultivated land area can be assumed. Under such scenario, increase in production is a demographic rather than a climatic process. After Tappan et al (2000), Tottrup and Rasmussen (2004) have also reported that in years of lacking rainfall farmers increase the area under cultivation so as to compensate for the crop yield deficit. Whatever the case, in all West African countries where agriculture has been extensive the acreage's increase is space-limited for it cannot be beyond the political frontiers.

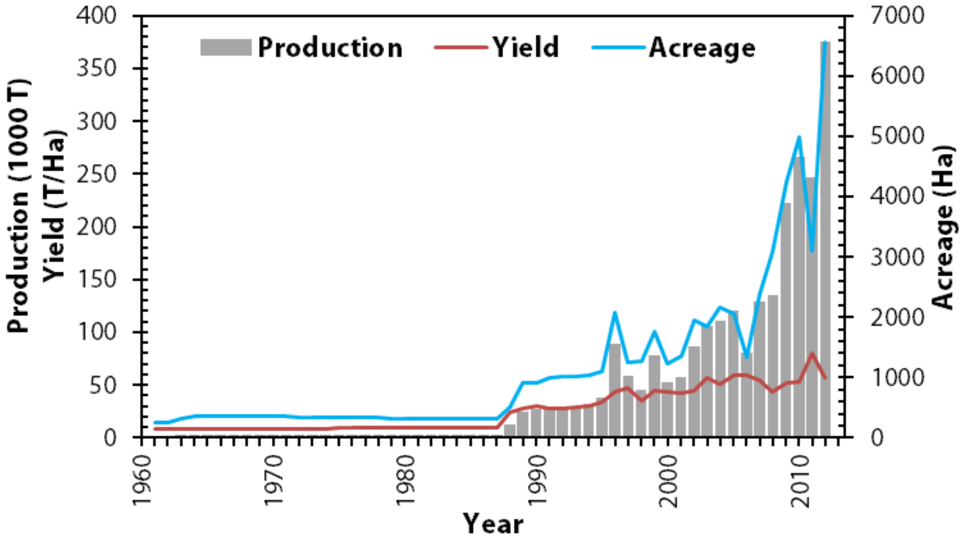


Figure 4.2: Pineapple statistics for Benin as shown in the FAOSTAT dataset.
Data source: FAOSTAT, 2014

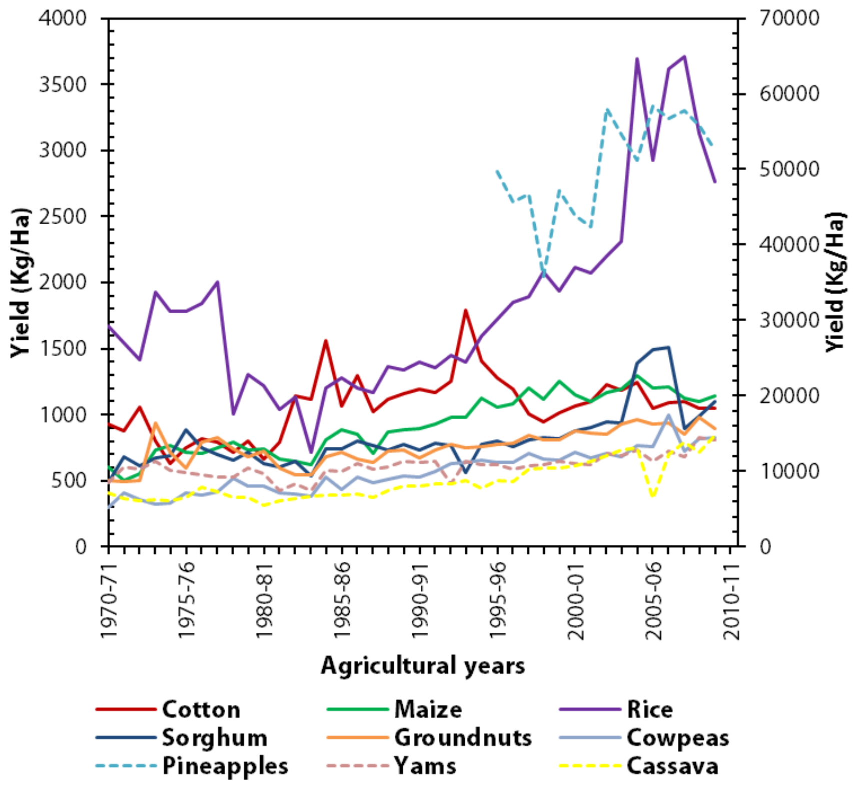


Figure 4.3: Observed time series of annual crop yields averaged over Benin.

The solid lines refer to the left scale, the dashed lines to the right scale of the ordinate.

Data source: MAEP's compendiums of agricultural statistics (MDR 2004; MAEP 2010)

For all the crops investigated, growing season months in Benin have been defined based mainly on contacts with agricultural extension services and the cropping calendar information from the FAO website (http://www.fao.org/agriculture/seed/cropcalendar/searchbycountry.do). Figure 4.4 presents the cropping calendar for each of the crops as considered for the study.

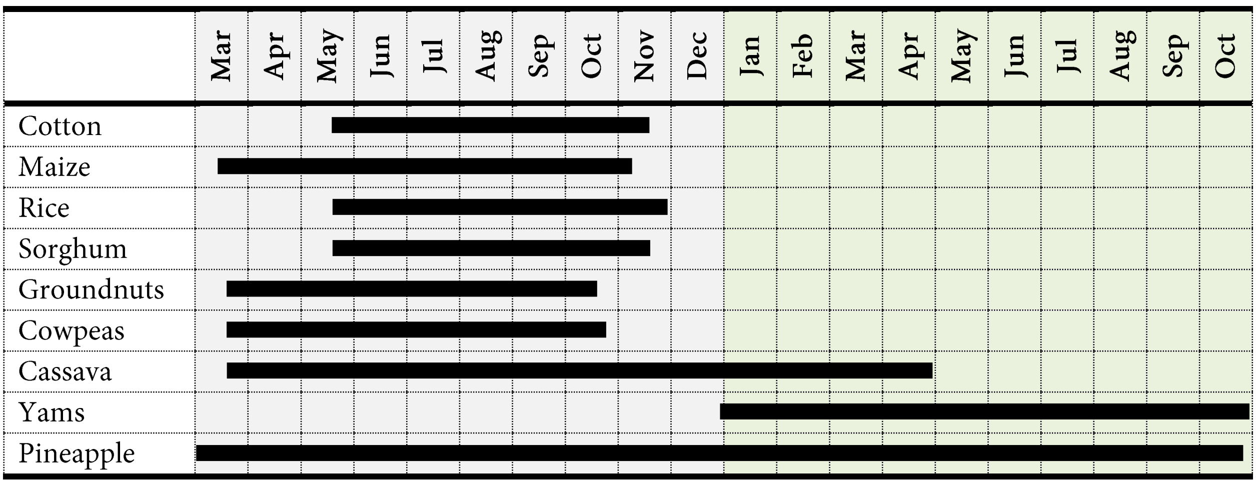


Figure 4.4: Cropping calendar for the crops considered in the study.

The bar indicates the duration from the sowing/planting to the beginning of the harvest of the crops that were planted late.

As shown in Figure 4.4, for most of the crops the sowing/planting starts at the beginning of the rainy season, except yams for which the land preparation starts late in the calendar year and then the planting is done beginning of January in the dry season. For most of the staple crops the growing seasons in the southern and the northern parts of Benin are combined. In fact, since agriculture in Benin is mainly rainfed, the starting and the length of the growing seasons of the staple crops depend on the onset and duration of the rainy season. Because of the bi-modal rainfall distribution in the south of the country, crop varieties with short production cycle (e.g. maize, groundnuts) are cultivated twice in a year in the southern part. Farmers in Benin benefit from little support from the agricultural extension services regarding the management of their cropping calendars. In response to the inter-annual climate variations, they adjust their cropping calendars by shifting either forward or backward the timing of the land preparation and the seedling, and thus all remaining agricultural activities also shift accordingly. For crops like maize, the farmers also practice a double sowing in case dry spells occur after the first sowing (Yegbemey et al 2014). Considering all the above, there is not a specific date for the beginning of the agricultural activities, but a period of time since each farmer manages the cropping calendar by him/herself. Therefore, the cropping calendar as shown spans the earliest sowing/plantation to the beginning of the late harvest in the year. This made it slightly different from those presented for some areas in the northern Benin by Yegbemey et al (2014) for maize and Forkuor et al (2014) for some more crops.

For a perennial crop like pineapple grown only in the southern part of Benin, the cropping calendar presented also lasts from the earliest planting to the beginning of the harvest of the crops that were planted late. In fact, the planting starts with the onset of the first rainy season in March. Although pineapple can be grown all over the year, the preferred planting time for both the cultivars Sugarloaf and Smooth Cayenne is March to June. The production cycle lasts between 14-19 months with on average 15.8 months for cv. Smooth Cayenne and 16.2 months for cv. Sugarloaf. The flowering is artificially induced 9-13 months after planting (Fassinou Hotegni et al 2010).

5 STATISTICAL METHODS

This chapter describes the methodology followed to develop the statistical crop models. It covers the pre-processing steps of the raw climate data and yield data (section 5.1), the generation of time series of principal components (section 5.2), and the development of the crop models in present-day as well as their transfer into the future with REMO RCM projections (mean of three ensemble-member runs) under three different SRES scenarios combining both GHGs and LCC (section 5.3). Different multi-model averaging techniques used are also explained in details (section 5.4) together with the evaluation criteria of the models (section 5.5). All the analyses in this study are performed with scripts written in the scientific programming language Fortran.

5.1 Data pre-processing

A pre-processing of the raw present-day and future climate datasets and their derived principal components (PCs) was performed before the development of the crop models. The following sub-sections present the various techniques and statistics used for this data pre-processing.

5.1.1 IDW interpolation

Although the REMO and CRU data used are both at regular 0.5° resolution, they do not show the same position for the grid box centres. Thus it was necessary to interpolate the original REMO data (3 single model ensemble-member runs × 3 scenarios) to the CRU grid. Many types of algorithms are developed to perform such spatial transformation. Among the existing algorithms, the Inverse Distance Weighting commonly called IDW interpolation was used. It belongs to the family of deterministic spatial interpolation methods and is widely known and applied in many environmental fields, including meteorology and climatology (Hartkamp et al 1999; Samanta et al 2012). IDW interpolation is an advanced nearest neighbour method that determines the unknown value at a point or grid box by a weighted average of the known values at "n" surrounding points or grid boxes (Watson and Philip 1985; Hartkamp et al 1999). The weights applied are non-linearly dependant on the linear distance separating the grid box from the "n" surrounding grid boxes in the original grid space. In this study six (6) nearby grid boxes (n = 6) were considered for the estimation. Assuming that $Y(t, s_y)$ is the interpolated variable in the new grid space and $X(t, s_x)$ a variable in the original grid space, for each new location s_y at the time t the function for IDW interpolation from known values at nearby locations s_x can be mathematically expressed as (Shepard 1968):

$$Y(t, s_y) = \frac{1}{\sum_{s_x=1}^{n} w(s_x)} \sum_{s_x=1}^{n} w(s_x).X(t, s_x) \qquad \text{Eq. 5.1}$$

Following this formula, the interpolated variable in the new grid space is a weighted average of values from the original dataset. The weights decrease as the distance increases (Watson and Philip 1985; Tugrul and Polat 2014). In fact, the weight functions $w(s_x)$ assigned are inverse d-power functions of the linear distance between the point that value is to be estimated and some surrounding points in the original grid space taken as estimators (Ly et al 2013). It is calculated as (Shepard 1968):

$$w(s_x) = \left(\frac{1}{d(s_y, s_x)}\right)^d \qquad \text{Eq. 5.2}$$

The power parameter d is to be selected before the interpolation is done. In this study that power parameter was set to 2 ($d = 2$), making the weighting an inverse-distance quadratic function.

5.1.2 Univariate descriptive statistics

The univariate descriptive statistics used in this study are arithmetic mean and weighted mean, weighted and unweighted variance / standard deviation and moving average.

- Weighted mean and arithmetic mean

Similar to Eq. 5.1 for spatial interpolation, in case the values of some observation points count more strongly than others in the dataset, the equation for the weighted average or weighted mean $\bar{X}_w$ can be expressed as:

$$\bar{X}_w = \frac{1}{\sum_{i=1}^{n} w_i} \sum_{i=1}^{n} w_i \, . X_i \qquad \text{Eq. 5.3}$$

where w_i is the weight associated to each observed value X_i from the variable X, and n the number of considered observations. In case the observed values are equally weighted, the mean is then called an arithmetic mean $\bar{X}$ and is expressed as:

$$\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i \qquad \text{Eq. 5.4}$$

Further details of what the weighted mean was used for are given in section 5.4.

- Variance and standard deviation

The variance is a statistical quantity used to measure the dispersion in a set of data points around the mean. Again, assuming that X_i is an observed value of the variable X, n the number of considered observations and $\bar{X}$ their mean, the variance $S_{n,X}^2$ can be expressed as:

$$S_{n,X}^2 = \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2 \qquad \text{Eq. 5.5}$$

Like the mean in Eq. 5.3, the variance can also be weighted in case some observations count more than others. The weighted variance $S_{w_{n,X}}^2$ can be written as:

$$S_{w_{n,X}}^2 = \frac{1}{\sum_{i=1}^{n} w_i}\sum_{i=1}^{n} w_i(X_i - \bar{X}_w)^2 \qquad \text{Eq. 5.6}$$

where the mean used here is the weighted mean from Eq.5.3 since each observation has got a weight w_i.

The variance is always a positive quantity. The square root of the variance is called the standard deviation ($S_{n,X}$ or $S_{w_{n,X}}$). Low values of variance/standard deviation indicate that the observations are close to the mean (little/no dispersion), while high values point to a large dispersion of the observations around the mean. The use made of the variance in this study is explained in details in the section 5.4.

- Moving average

Also called running average or running mean, the moving average is a filtering technique used to remove the fluctuations of low frequency from time series. Here the moving average is computed in a way that on the chosen window the mean is computed from an equal number of data at each side of a central value. Thus the length of the window is taken to be an odd number. Assuming that X_j are the original time series and X_i' are the low-pass filtered data the moving average on k-window can be expressed as:

$$X_i' = \frac{1}{k}\sum_{j=i-(k-1)/2}^{i+(k-1)/2} X_j \qquad \text{Eq. 5.7}$$

In this study the moving average was used to remove short term fluctuations from both climate and predicted yield data before plotting them.

5.1.3 Trend detection and removal

The time series of national crop yields often exhibit an increase over time due to improvements in crop production technology (Osborne and Wheeler 2013). This is true for the yield statistics used in this study as well. To remove the effects of the technological improvements, the yield data were detrended. This trend removal was done prior to the correlation of the yield data with all observed monthly principal components (monthly PCs from CRU data) for the purpose of selecting potential climate predictors. As well, in the statistical crop models, trend was also removed from the potential climate predictors. This was done to ensure that the technological trend in the original yield data did not influence the selection of the potential climate predictors, and in the crop models the linear relationship between the predictand (yield) and the predictors (potential climate predictors) was built on only their year-to-year variations (i.e. long-term variations are removed and thus did not influence the correlations).

Two approaches are quite often used to remove a trend from any observational dataset. These are: (1) fitting a trend and considering the residuals, and (2) deriving first differences (i.e. difference from one year to the next) (Lobell and Field 2007; Osborne and Wheeler 2013; Sultan et al 2014). In this study, the first approach was used but just a first-order polynomial trend approximation was considered. This means, a simple linear regression was performed between the considered variable Y taken as explained variable and the rank of each of its observations or the years taken as explanatory variable X. In other words, a straight line (linear trend line) is fitted through the n data points of the Y variable in a way that the vertical distances from the data points to the fitted line is minimised. The linear regression model takes the form:

$$\vec{Y} = f(X) = a\vec{X} + b \qquad \text{Eq. 5.8}$$

where a is the slope of the regression and b the constant of the regression.

For the derivation of the two coefficients of this regression (Eq.5.8), a mathematical issue arises. This issue is to find in the ensemble of functions $\mathcal{G}$, the function f that minimises a cost function $l(.)$. Mathematically, this minimisation issue can be written as:

$$\underset{f \in \mathcal{G}}{\arg min} \sum_{i=1}^{n} l\big(Y_i - f(X_i)\big) \qquad \text{Eq. 5.9}$$

To solve the problem, two minimisation approaches are commonly used. Assuming that $u = Y_i - f(X_i)$ and $l(u)$ is the cost function to be minimised, either one minimises the sum of the vertical distances between the fitted line and the data points (i.e. absolute cost function: $l(u) = |u|$), or one minimises the sum of the square of the vertical distances between the fitted line and the data points (i.e. quadratic cost function: $l(u) = u^2$). In this study, an ordinary least square estimation method (OLS) was selected for this purpose. This means that the quadratic cost function has to be minimised. Then the system of equations to be resolved can be expressed as (Cornillon and Matzner-Løber 2007):

$$\begin{cases} \dfrac{\partial l(a,b)}{\partial b} = -2\displaystyle\sum_{i=1}^{n}(y_i - b - aX_i) = 0 \\ \dfrac{\partial l(a,b)}{\partial a} = -2\displaystyle\sum_{i=1}^{n}X_i[(y_i - b - aX_i)] = 0 \end{cases} \qquad \text{Eq. 5.10}$$

By resolving the system of equations (Eq. 5.10), the two unknown coefficients are then derived as follows:

$$a = \frac{cov(X,Y)}{\left(S_{n,X}^2 \times S_{n,Y}^2\right)^{1/2}} \qquad \text{Eq. 5.11}$$

$$b = \bar{Y} - a\bar{X} \qquad \text{Eq. 5.12}$$

$S_{n,X}^2$ and $S_{n,Y}^2$ are obtained according to Eq. 5.5 while the calculation of $\bar{X}$ and $\bar{Y}$ followed Eq. 5.4. The covariance $cov(X,Y)$ is computed as:

$$cov(X,Y) = \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X}) \times (Y_i - \bar{Y}) \qquad \text{Eq. 5.13}$$

Once the trend is obtained, the residuals are calculated and considered later. Let Y_i' be the detrended value for each data point. The trend removal is then finally performed for each data point as follows:

$$Y_i' = \hat{\varepsilon}_i = Y_i - (aX_i + b) \qquad \text{Eq. 5.14}$$

5.1.4 Time series correlation

Correlation is one of the most used statistical tools in climate research and other natural sciences branches. Herein Pearson's correlation coefficients were used to assess the degree of linear relationship between historical crop yield and individual observed monthly principal components (i.e. monthly PCs of observed precipitation and mean air temperature), so as to select potential climate predictors for the statistical crop models. Assuming that X and Y are the two covariates to be correlated, the Pearson correlation coefficient r_{XY} is then defined as (Pearson 1896; Mudelsee 2010):

$$r_{XY} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{X_i - \bar{X}}{S_{n,X}}\right).\left(\frac{Y_i - \bar{Y}}{S_{n,Y}}\right) \qquad \text{Eq. 5.15}$$

with $\bar{X}$, $S_{n,X}$, $\bar{Y}$ and $S_{n,Y}$ standing for the sample means and standard deviations of the X and Y covariates respectively. This estimator varies between -1 and 1 with values close to 1 (-1) indicating a high positive (negative) linear association between the covariates while values close to 0 point to a low linear association. The square of this correlation coefficient is called coefficient of determination r_{XY}^2 and expresses the percentage of variation of the dependant variable (Y) explained by the variation of the independent variable (X).

5.1.5 Statistical inference

The Student t-test was used to check the statistical significance of the correlation coefficients. Indeed, for the development of the crop models only the observed monthly PCs for which correlations with the observed yields was found to be significant at 5% were considered as potential predictors. But for the pineapple crop model 1% significance level was retained.

For this test the hypotheses are:

$H_0 : \rho = 0$ (no correlation between X and Y variables), and

$H_1 : \rho \neq 0$ (statistically significant correlation between the variables)

Following these hypotheses and for each of the crop yield – observed monthly PC combination the estimated test statistics $\hat{t}$ at n-2 degree of freedom are computed as follows:

$$\hat{t} = r_{XY} \times \left(\frac{n-2}{1-r_{XY}^2}\right)^{1/2} \qquad \text{Eq. 5.16}$$

The absolute values of the test value $|\hat{t}|$ are then compared to the critical values T of the two-tailed student's t distribution at n-2 degree of freedom and p significance level (p=0.01 or 0.05). In case $|\hat{t}| \geq T$ the null hypothesis is rejected. Thus its alternative H_1 is accepted and the considered monthly principal components can be retained as potential climate predictors for the crop model.

5.2 Principal components analysis

In this study, the crop models are driven by large scale and/or smaller scale climate information. This information is obtained by means of Principal Components Analysis (PCA). Also called Empirical Orthogonal Functions (EOF) analysis, PCA is a technique used to reduce the dimensionality of a large multivariate dataset through creation of new variables that summarize the information contained in the original dataset. In principle the new variables are linear combinations of the original ones and they are built in such a way that they are orthogonal from one another and the amount of variability in the original dataset explained by each new variable decreases as the order of the variables increases. PCA can also be applied to a univariate dataset with various spatial units like gridded dataset of temperature, precipitation or any atmospheric data. Thus the various spatial units replace the variables.

Here, PCA was applied to the CRU data and all the interpolated REMO data (3 ensemble-member runs × 3 scenarios). The considered data were 0.5° grid resolution monthly precipitation and mean air temperature for all land masses in the domain extending over 0° - 40°N and 20°W - 40°E, thus the number of grid points m equals 7433. The method described below was applied exactly the same way to the precipitation and mean air temperature datasets. The term variable used in this section denotes both precipitation and mean air temperature. In fact, observed patterns and PCs were derived from the CRU data. Then the REMO data were projected on the observed patterns to obtain the simulated PCs. Prior to these analyses all the datasets were weighted by the cosine of the latitude of each grid point. For each grid point s the weights $w(s)$ applied were calculated as follows:

$$w(s) = \sqrt{\frac{cos[lat(s)]}{\sum_{s=1}^{m} cos[lat(s)]}}\ , s = 1, 2, \ldots, m \qquad \text{Eq. 5.17}$$

Once the weighting coefficients were obtained, the PCA was performed for the CRU and REMO datasets as described in the following sub-sections.

5.2.1 PCA of the observational climate data

As introduced in section 4.1, the CRU data used spans from 1901 to 2010 and was composed of monthly data of air temperature and precipitation. So the time step $t = 1, 2, \dots, n$ with $n = 1308$. Prior to the PCA annual cycles were calculated and subtracted from the CRU data for each month per grid point. Let $X(t, s)$ represent the new data with annual cycles removed. In practice, PCA is performed on either a correlation matrix or a covariance matrix. In this study, the covariance matrix was used because it allows identifying the strongest variations in the dataset contrary to the correlation matrix in which the spatial variations in the dataset are removed (Wilks 2011). Hence, per grid point s the data were transformed as follows:

$$X'(t, s) = w(s).\left(X(t, s) - \bar{X}(s)\right) \qquad \text{Eq. 5.18}$$

Here $\bar{X}(s)$ represents the arithmetic mean (Eq. 5.4) per grid point.

Basically the goal of PCA is to find the set of new variables or principal components $\vec{u}_i(t)$ that summarise the information in the data $X'(t, s)$, together with their associated variability modes or eigenvectors $\vec{e}_i(s)$. Knowing those principal components time series and eigenvectors at any time the data can be reconstructed as follows (Von Storch and Zwiers 2004):

$$X'(t, s) = \sum_{i=1}^{m} \vec{u}_i(t).\vec{e}_i^{\,T}(s) \qquad \text{Eq. 5.19}$$

In principle, before obtaining the principal components a main mathematical issue has to be solved. Indeed, the mathematical issue that arises here is to find the eigenvectors $\vec{e}_i(s)$ and the associated eigenvalues λ_i. This yield a system of equations that can be expressed as (Von Storch and Zwiers 2004):

$$\underset{(m \times m)}{A} \times \underset{(m \times 1)}{E} = \lambda \times \underset{(m \times 1)}{E} \qquad \text{Eq. 5.20}$$

Since the dataset contains m grid points, Eq. 5.19 should be resolved m times. In fact, starting first with the covariance matrix of the data ($A = {X'}^T X'$) Eq. 5.20 has to be solved and the first eigenvector $\vec{e}_1(s)$ and its eigenvalue λ_1 obtained. This first eigenvector will have the largest variance. Subsequently the matrix A should be recomputed each time after subtracting the information explained by the ith eigenvector and the next eigenvector ($[i + 1]$th) with the largest possible variance can be calculated together with its eigenvalue. Moreover, all the eigenvectors should be uncorrelated and thus can be denoted empirical orthogonal functions

(EOFs). The share of information holds by each eigenvector or the variance explained by each eigenvector $\vec{e}_i(s)$ can be expressed as:

$$R_i^{\ 2} = \frac{\lambda_i}{\sum_{i=1}^{m} \lambda_i} \qquad \text{Eq. 5.21}$$

In general, the variance explained by each eigenvector decreases as the index of the eigenvector increases (see Figure 5.1). The mathematical issue in Eq. 5.20 was solved with software implementations in the Rogue Wave's International Mathematical and Statistical Library (IMSL). Thanks to the EVCSF subroutine of the Fortran IMSL Numerical Libraries that served to compute all the eigenvalues and eigenvectors from the real symmetric matrix $X'^T X'$ (Rogue Wave SOFTWARE 2012).

Figure 5.1Figure 4.1 shows the amount of information (eigenvalues in %) held by each of the 50 leading empirical orthogonal functions. The first EOF of precipitation explains about 8.4% of information whereas the first EOF of air temperature holds about 32% of information. The variance explained by each EOF decreases with the increasing order of the EOFs. All together the leading four EOFs of precipitation and air temperature explained about 22.5% and 66.7 % of global information respectively whereas the leading 20 EOFs holds about 49.9% and 90% of global information respectively.

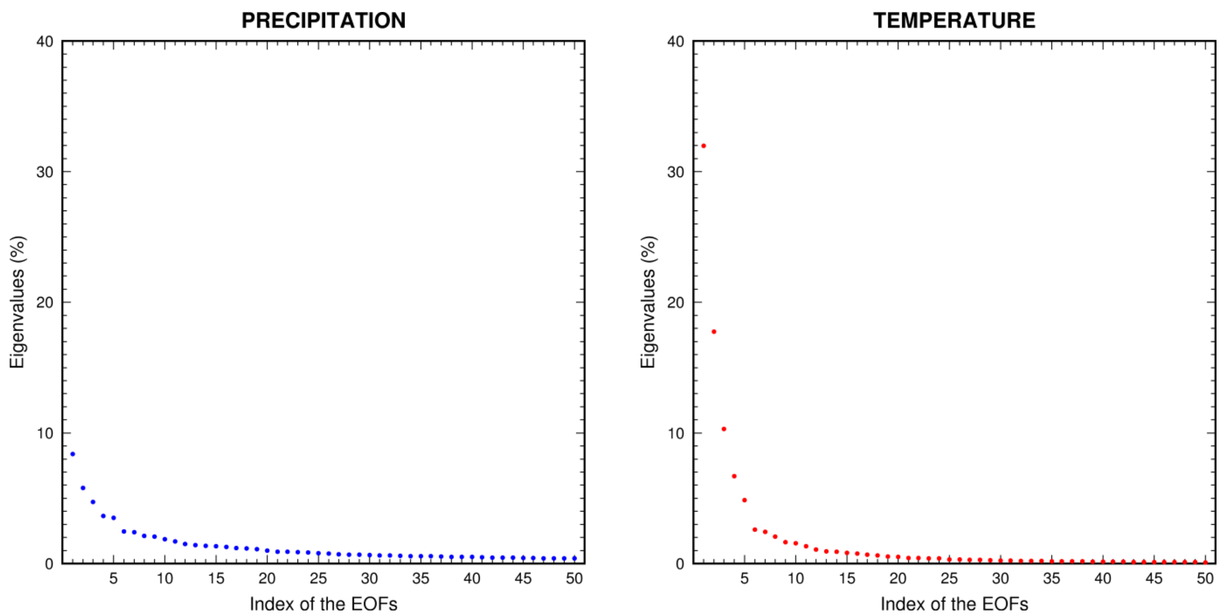


Figure 5.1: Shares of variance explained by each of the leading 50 EOFs of precipitation and mean air temperature.

Once the eigenvectors were all obtained they were further normalized ($\|\vec{e}_i\| = 1$) and sorted. For each eigenvector $\vec{e}_i$ the normalisation implies that:

$$\sum_{s=1}^{m} e_i{}^2(s) = 1 \qquad \text{Eq. 5.22}$$

Therefore, the observed principal components were computed. Each principal component $u_i(t)$ was the result of the projection of the data $X'(t,s)$ onto the ith eigenvector. Mathematically, this projection can be expressed as (Von Storch and Zwiers 2004):

$$u_i(t) = \sum_{s=1}^{m} e_i(s) \times X'(t,s) \qquad \text{Eq. 5.23}$$

Each PC $u_i(t)$ holds the same amount of information as the EOF $e_i(s)$ it is generated from. In the following the principal components obtained from the CRU data are denoted observed PCs or CRU PCs whereas the eigenvectors are called observed EOFs.

5.2.2 Principal components time series derivation for the simulated climate data

As introduced in section 4.2, the simulated REMO data used are monthly precipitation and air temperature. These datasets extend from 1960-2000 in present-day to 2001-2050 in the future. In present-day, one scenario is available whereas three scenarios are available for the future. For each of these scenarios three ensemble-member runs were available and used (refer section 4.2). Therefore simulated principal components were derived from every run of each scenario. This means a set of three PCs time series of index i was obtained for each scenario of temperature and precipitation. Let's assume that $X(t,s)$ represents a dataset of a specific run. Contrary to the observed CRU data, seasonality does not need to be removed from the simulated REMO data. The dataset $X(t,s)$ were directly transformed to a new weighted anomalies dataset $X'(t,s)$ according to Eq. 5.18. Therefore, the data $X'(t,s)$ were projected onto the observed EOFs patterns $\vec{e}_i(s)$ to get the simulated principal components $u_i(t)$. This projection was done according to Eq. 5.23.

Since the projection was done for all the three ensemble-runs per scenario, for each scenario three PCs of index i were obtained. Per scenario the three PCs of ith order were averaged to return an ensemble-mean of ith order PC. These ensemble-mean PCs were considered to develop the crop-models. In the following they will be referred to as simulated PCs or REMO PCs.

5.3 Development of the crop models

Statistical crop models are developed for nine crops namely pineapple, cotton, maize, rice, sorghum, groundnuts, cowpeas, yams, and cassava. The models are based on multivariate regression analysis. It has become common practice to use multivariate regression models to explain changes in agricultural outputs as a result of seasonal changes in climate variables (Chen et al 2004; Isik and Devadoss 2006; Schlenker and Roberts 2006; Sheehy et al 2006; Tao et al 2006; Lobell 2007; Lobell and Field 2007; McCarl et al 2008; Tannura et al 2008; Kim and Pang 2009; You et al 2009a; Schlenker and Roberts 2009; Schlenker and Lobell 2010; Welch et al 2010; Lobell and Burke 2010; Lobell et al 2011b). As well, in times of climate change multivariate regression models find again their use by helping to predict changes in agricultural outputs that can result from future changes in the dynamical climate forecasts. Such prediction is important to quantify the possible impacts of future climate change in agriculture (i.e. to measure the potential risks), develop early warning systems and formulate adaptation options, or review the on-going adaptation options (Rowhani et al 2011; Lobell et al 2011b; Bhatt et al 2014).

In this study the models developed are more specifically based on multivariate linear regression (MLR). MLR is used to establish the linear relationship between a dependent variable (predictand) and a set of independent variables (predictors). Let us call “P1” the time period during which historical yield data are available for each crop and used to develop the models. For pineapple this period “P1” corresponds to the crop production years 1995/96 through 2008/09 (14 years). But for all other crops it corresponds to the production years 1970/71 to 2009/10 (40 years). For inter-crops comparison another time period “P2” served as reference. Since the yield data for pineapple are the smallest in size then the time period “P2” for comparison corresponds to the crop production years 1995/96 to 2008/09. It must be stated that for each crop the yield of a given crop production year is counted for the calendar year in which the entire harvest or the bulk of it took place. This means that per example for the crop production-year 1995/96 the yield of crops like pineapple that are grown over two calendar years are counted for the calendar year 1996 whereas the yield of all the other crops that are grown is one calendar year period is counted for 1995. As pointed out by Breiman (2001) and Yu et al (2013) the purpose of most statistical analysis is description and prediction. Statistical methods are used to look for the important factors and to investigate the relationship between those factors and the quantity of interest. The collected information is further used to inform the future. In the same vein the development of the crop models has followed these consecutive steps:

(1) Selection of the potential climate predictors

(2) Construction of the statistical crop models in present-day with the observed climate predictors and predictand. The crop model is based on multiple linear regression (MLR) combined with cross-validation and bootstrap resampling of the predictand and predictors.

(3) Transfer of the crop model to REMO. That is, the developed crop model was forced with the simulated climate predictors for present-day and future.

5.3.1 Selection of the potential climate predictors

In order to find out the potential climate predictors for each crop model the historical yields of the considered crops were correlated with the leading 20 PCs of observed monthly precipitation and mean air temperature during the time period P1. As early stated in section 5.1.3, the yield data was linearly detrended before these correlations. For each crop yield-monthly climate PCs combination, the statistical significance of the correlation coefficients was tested. The PCs for the months in the crop growing season (defined in the crop calendar, Figure 4.4), and for which correlations with the yield were found to be statistically significant at a least 5%, were retained as potential climate predictors. With these selection criteria, the selected potential predictors were more than the time series of pineapple yield. While keeping this number of predictors, the matrix for MLR could not be inverted. Thus, for pineapple the selection criteria was changed from 5% significance to 1% so that the number of potential predictors could be less than the size of the historical yield time series used to train the model.

5.3.2 Non-parametric bootstrap resampling of the predictand and predictors

Non-parametric bootstrap resampling was used to estimate the uncertainty in the fitted regression models (Ramankutty et al 2008). Bootstrap resampling often combines a uniform random numbers generator with a resampling algorithm (Efron and Gong 1983; Wilks 2011). In principle, the bootstrap resamples hold all the statistical properties of the original datasets (Mudelsee 2010) taken as population from which samples are to be drawn. The datasets are iteratively split into two partitions. In this study, 1000 bootstrap runs were performed. Assuming that n is the size of the observed predictors and predictand variables, n_A observations are used to train the crop models and n_B observations for validation. For each of the 1000 bootstrap runs, a sample of four independent observations were randomly selected for cross-validation (n_B=4). Generally, bootstrap resampling are performed with replacement (Wilks 2011). But here for each bootstrap resample, the algorithm used was developed in such a way that the n_B randomly selected observations are different (no replacement). For each random resample, the observations are selected one by one. The first random observation $ran(1)$ is selected among n. Then each subsequent random observation $ran(i)$, $i = 2, \dots, n_B$ is selected in such a way that it is different from those previously selected ($ran(i) \neq ran(i-1)$). For each bootstrap sample of size n_B, the one by one resampling method can be mathematically expressed as:

$$ran(i) = 1 + int(ran0(c) \times n)\ ; i = 1, \dots, n_B \qquad \text{Eq. 5.24}$$

where $ran(i)$ is the bootstrap observation obtained, $ran0(.)$ a random number generated with the uniform random number generator, c the seed defined at each bootstrap run, and $int(.)$ stands for the integer part. The uniform random number generator returns random real numbers $ran0$ in the interval $]0, 1[$. Starting with the value 1 the seed c was incremented by 1000 at each following bootstrap run. Once the four random sets of values for cross-validation were selected, they were removed from the original dataset and the remaining was used to train the crop models. Therefore it can be considered that the bootstrap resampling yields 1000 samples of n_A independent observations for training the model and 1000 random resamples of n_B independent observations for cross-validation.

5.3.3 Multivariate linear regression applied for yield modelling

The statistical relationships between the agricultural yields and the potential climate predictors were investigated by means of cross-validated multiple linear regression applied to each bootstrap resample. Basically the MLR function can be mathematically expressed as:

$$\vec{Y} = X.\vec{\beta} + \vec{\varepsilon} \qquad \text{Eq. 5.25}$$

where $\vec{Y}$ is the predictand time series (dependant variable), X is the matrix of predictor time series (with unit vector in the first column for the p independent variables in the other columns), $\vec{\beta}$ is the vector of regression coefficients to be estimated and $\vec{\varepsilon}$ the unpredicted part of the predictand (i.e. error term to be minimised). Assuming that p predictors of size m are used in the regression the function can be rewritten as (Paeth et al 2008a; Schmidt et al 2013):

$$Y_j = \hat{Y}_j + \varepsilon_j = \beta_0 + \sum_{i=1}^{p} \beta_i X_{ji} + \varepsilon_j \qquad \text{Eq. 5.26}$$

With $\vec{Y} = \begin{pmatrix} Y_1 \\ \vdots \\ Y_j \\ \vdots \\ Y_m \end{pmatrix}$; $X = \begin{pmatrix} 1 & X_{1,1} & \cdots & X_{1,i} & \cdots & X_{1,p} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & X_{j,1} & \cdots & X_{j,i} & \cdots & X_{j,p} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \beta_{m,1} & \cdots & \beta_{m,i} & \cdots & \beta_{m,p} \end{pmatrix}$; $\vec{\beta} = \begin{pmatrix} \beta_0 \\ \vdots \\ \beta_j \\ \vdots \\ \beta_p \end{pmatrix}$ and $\vec{\varepsilon} = \begin{pmatrix} \varepsilon_0 \\ \vdots \\ \varepsilon_j \\ \vdots \\ \varepsilon_p \end{pmatrix}$

Also called regression parameters, the regression coefficients $\vec{\beta}$ were estimated following ordinary least squares (OLS) fitting. This is equivalent to minimising the sum of square errors $SS\varepsilon$ which is determined by (Von Storch and Zwiers 2004):

$$SS\varepsilon = \vec{\varepsilon}^T \vec{\varepsilon} = \left(\vec{Y} - X\vec{\beta}\right)^T \left(\vec{Y} - X\vec{\beta}\right) \qquad \text{Eq. 5.27}$$

Similar to Equation 5.10 for the case of simple linear regression, as well a system of p+1 equations was solved. In fact, as the matrix X is composed of p+1 variables p+1 first partial derivatives of the $SS\varepsilon$ function were simultaneously resolved to get the regression parameters. The estimated regression parameters for the MLR function are finally (Paeth and Hense 2003; Von Storch and Zwiers 2004; Paeth et al 2008a):

$$\hat{\vec{\beta}} = (X^T X)^{-1} X^T \vec{Y} \qquad \text{Eq. 5.28}$$

The performance of an estimated MLR function is commonly assessed by computing a coefficient of multiple determination R^2. This R^2 expresses the percentage of the variation of the response variable $\vec{Y}$ that is explained by the model as developed (i.e. all the chosen predictors together with their associated parameters and the intercept). In other words it shows how the estimated model fits the data. The R^2 coefficient always varies between 0 and 100% with higher values indicating a better fit.

In this study, both the observed predictors and predictand were linearly detrended (as described in section 5.1.3) in order to avoid trend based correlation (Paeth and Hense 2003). The models were built with the standardized anomalies (relative to the time period P1) of those predictors and predictand. As uncertainty is inherent to any estimation, here bootstrap technique served for the estimation of the uncertainty in the estimates of regression parameters and thus the crop model (Ramankutty et al 2008). For each of the crops studied 1000 bootstrap runs (iterations) of the standardised predictors and potential predictors, each with n values, were performed following the procedure previously explained in section 5.3.2. It returned 1000 sets of resamples training and validation data of size respectively n_A and n_B $(n = n_A + n_B)$. Thus per crop the regression model in equation 5.25 or 5.26 was re-estimated 1000 times.

For each of the 1000 iterations the sample of $n_A$observations of the predictand and potential predictors was used to train a model. The simplest form of a stepwise screening scheme called forward selection approach was followed for data-driven into the model. With this screening approach the potential predictors are put into the model one at a time. At each regression step k ($k = 1, \dots, p$) each potential predictor is tested for inclusion into the model and the most important of these predictors with respect to the predictand is added to the model. Generally, the predictor with the lowest p-value below 0.10 or 0.15 is included. But herein instead of basing the inclusion criteria on the lowest p-value highest coefficient of determination following Pearson correlation (Eq. 5.15) is used. At the first regression step, beginning with an empty model, all potential predictors are correlated with the predictand and the one with the highest R^2 is defined to be the factor of highest rank. Then the matrix X starts with the unit vector and the time series of this predictor and a simple linear regression is fitted. The OLS estimation returns the parameters β_0 (constant term) and β_1 (slope). The R^2 of the fitted model is calculated following Eq. 5.15 applied with the values of Y_j and $\hat{Y}_j$. The prediction error is measured by the mean square error (MSE_M) (Paeth and Hense 2003; Von Storch and Zwiers 2004).

$$MSE_M = \frac{1}{n_A}\sum_{j=1}^{n_A}\left(Y_j - \hat{Y}_j\right)^2 \qquad \text{Eq. 5.29}$$

At any regression step k the error term of a fitted model can be expressed as (Von Storch and Zwiers 2004):

$$\varepsilon_j = Y_j - \hat{Y}_j = Y_j - \left(\beta_0 + \sum_{i=1}^{k}\beta_i X_{j,i}\right) \qquad \text{Eq. 5.30}$$

Having fitted a model with the first selected predictor, the predictor inclusion procedure is iteratively repeated until all the remaining predictors are added. At each subsequent regression step k, $k = 2,3 \dots, p$, the unpredicted part of the predictand ε_j ($j = 1 \dots n_A$) from the model fitted at the step $k - 1$ is now correlated with the remaining predictors. Then the predictor having the highest possible R^2 is given priority for inclusion and added to the matrix X. The matrix X is then giving the size $n_A \times (k + 1)$. The new matrix being constructed, the MLR is fitted again. This yields a new set of regression parameters. The R^2 of the new model is calculated again together with the MSE_M.

A cross-validation is later used to cut-off the predictors that do not add further information to the models. At each regression step the independent sample of size n_B retained for cross-validation is used to evaluate the model via a control mean square error (MSE_C). Thus in Eq. 5.31 Y_j and $\hat{Y}_j$ stand respectively for the control data and their estimated values (Paeth and Hense 2003; Von Storch and Zwiers 2004).

$$MSE_C = \frac{1}{n_B}\sum_{j=1}^{n_B}\left(Y_j - \hat{Y}_j\right)^2 \qquad \text{Eq. 5.31}$$

MSE_M was found to decrease with each additional predictor. But MSE_C normally decreases with each additional predictor but starts increasing after the optimal predictors are obtained. Thus the first minimum of the MSE_C defines the optimal number of predictors and shows at which step the regression parameters are to be considered for each iteration (Paeth and Hense 2003; Paeth et al 2006).

Different multi-model averaging techniques were applied to average the estimated yields or yield changes from the 1000 iterations per crop. These techniques included: arithmetic mean, weighting based on the adjusted coefficient of determination $\bar{R}^2$, corrected Akaike Information Criteria (AICc), Bayesian Information Criteria (BIC), Bayesian model averaging (BMA), and an automatic Bayesian model averaging (ABMA). The multi-model averaging techniques are described in details in section 5.4. The final averaged model (combined model) was assessed using as evaluation metrics the root mean square error (RMSE), the coefficient of determination (R^2), and Brier skill score (BSS) of the multi-model average. These metrics for model evaluation are described in section 5.5.They also served to compare the multi-model averaging techniques. The 1000 estimates of the regression parameters are documented and used to obtain the bootstrap distribution of each partial regression parameter. In addition, the 1000 estimates of yield served to define a robust confidence interval around the multi-model mean. Taking $CI_{95\%}$ for the 95 % confidence interval it is calculated at each time step as (Eq. 5.32):

$$CI_{95\%} = (\bar{Y}_w - 1.96 \times S_{w_{n,Y}}; \bar{Y}_w + 1.96 \times S_{w_{n,Y}}) \qquad \text{Eq. 5.32}$$

where $\bar{Y}_w$ and $S_{w_{n,Y}}$ stand respectively for the average yield or average yield change from the combined model and its corresponding standard deviation. Here the standard deviation $S_{w_{n,Y}}$ stands directly as the standard error because it is computed from 1000 estimates of yield. 1.96 is an approximation of the 97.5 percentile of the standard normal distribution.

The models developed with observed climate predictors from CRU were further transferred to REMO RCM. For this transfer the equivalent REMO monthly PCs (1960-2050) were also standardised. In fact, instead of using the mean and standard deviation from the CRU PCs, mean and standard deviation relative to the same time period P1 were calculated again for each of the relevant REMO PCs and used to get the standardised anomalies. Besides balancing out the unit of the predictors, the standardisation was done in that way for REMO to correct the REMO PCs for mean and variance. Thus relative to the time period P1, the observed predictors and the simulated ones have all means and variances equal to 0 and 1 respectively.

Since the models are built with standardised anomalies of the predictand and predictors their outcomes then express a departure from a mean by n times a standard deviation (relative to the time period P1). These estimates were converted to real yield data as follows (Eq. 5.33):

$$Y_i = (Y_i' \times S_{n-1,Y}) + \bar{Y} \qquad \text{Eq. 5.33}$$

In Eq. 5.33, Y_i represents the yield data in kg/Ha, Y_i' are the direct estimates from the crop model, and $\bar{Y}$ and $S_{n-1,Y}$ are respectively the mean and the standard deviation of the observed predictand relative to the time period P1 used to develop the crop models.

For inter-crops comparison the percentage of yield change was calculated relative to the time period P2. Thus at a time i the yield change ΔY_i relative to the period P2 can be expressed as:

$$\Delta Y_i = \frac{Y_i - \bar{Y}(P2)}{\bar{Y}(P2)} \times 100\% \qquad \text{Eq. 5.34}$$

Where $\bar{Y}(P2)$ is the average of the observed yields relative to the time period P2. This latter expression for yield change directly expresses the yield variation (gain or loss) in percentage and thus is more convenient to compare the variation of yield for different crops in time.

5.4 Weighting methods for multi-model averaging

Many studies have proven the superiority of a combined model (multi-model average) over a single best model (Raftery 1996; Raftery et al 1997; Hoeting et al 1999; Liang et al 2001). It was shown that better skill, higher reliability and consistency are obtained when several independent models are combined (Raftery et al 1997; Doblas-Reyes et al 2003; Yun et al 2003; Hagedorn et al 2005; Tebaldi and Knutti 2007; Cheng and AghaKouchak 2015). There are different ways to combine multi-models ranging from simple average in which the models are equally weighted to other classical statistics for weighting and more complex Bayesian methods where the weights are based on the relationship between observations and model estimates in the reference period (Tebaldi et al 2005; Tebaldi and Knutti 2007). Tebaldi and Knutti (2007) argue that it makes sense to weigh more the better models. But the difficulty is in defining the best way to quantify model skill and thus derive model weights accordingly. In this study the 1000 single models under consideration per crop were combined following different multi-model averaging methods namely simple average, weighting with the adjusted R square, Akaike weights, Bayesian information criteria, Bayesian model averaging and automatic Bayesian model averaging. These different weighting methods were applied to the pineapple crop model and the one found more robust relative to the evaluation criteria (i.e. R^2 and BSS of the combined model) was selected and applied for the other crop models. The following sub-sections described these methods. In those sub-sections let's denote $E(\Delta)$ or $E(\Delta|\mathrm{D})$ the quantity of interest (yield or yield change at a given time) and D the data, M_i represents a model for D, Δ_i an estimate of Δ based on the model M_i, and $P(M_i|D)$ or $P(M_i|Y)$ the posterior probability associated to the model. The likelihood of the model M_i is represented by $P(D|M_i)$ or $P(Y|M_i)$. B is the number of all models under consideration (herein $B = 1000$ if not stated).

5.4.1 Simple averaging

The simple average is similar to the arithmetic mean in Eq. 5.4. This means that the estimates from the different models are equally weighted. Thus the formula for deriving the quantity of interest is (Eq. 5.35):

$$E(\Delta) = \frac{1}{B}\sum_{i=1}^{B} \Delta_i \qquad \text{Eq. 5.35}$$

5.4.2 Weighting based on the adjusted coefficient of determination

For this multi-model averaging method the multiple coefficient of determination is first computed for every single model. Mathematically the multiple coefficient of determination $R^2_{(i)}$ of the model M_i can be expressed as (Eq. 5.36):

$$R^2_{(i)} = \frac{\left[\sum_{j=1}^{n}(Y_j - \bar{Y})\left(f_j^{(i)} - \bar{f}^{(i)}\right)\right]^2}{\left[\sum_{j=1}^{n}(Y_j - \bar{Y})^2\right] \times \left[\sum_{j=1}^{n}\left(f_j^{(i)} - \bar{f}^{(i)}\right)^2\right]} \qquad \text{Eq. 5.36}$$

where Y_j and $\bar{Y}$ denote respectively the observed yield data used to build the model (reference period P1 with $j = 1, \ldots, n$) and the mean of those observed yields over the time period P1. $f_j^{(i)}$ represents an estimate from the model M_i at a time j, and $\bar{f}^{(i)}$ is an estimate of the average yield also over the reference period P1 and from the model M_i.

In multiple linear regression the coefficient of determination of a model is prone to increase when additional predictors are added to the model. Thus the R square is not a good criterion to compare models having different numbers of predictors. Adjusted for the number of terms in each regression model the adjusted R square takes into account this problem of weak inflation of the R square, and thus allows comparison of different models. For each model M_i, the adjusted coefficient of determination $\bar{R}^2_{(i)}$ can be expressed as (Eq. 5.37):

$$\bar{R}^2_{(i)} = 1 - \frac{\left(1 - R^2_{(i)}\right)(n-1)}{n-p-1} \qquad \text{Eq. 5.37}$$

with p the number of free parameters in the model M_i.

The quantity of interest can then be calculated as (Eq. 5.38):

$$E(\Delta) = \frac{\sum_{i=1}^{B} \bar{R}^2_{(i)} \times \Delta_i}{\sum_{i=1}^{B} \bar{R}^2_{(i)}} \qquad \text{Eq. 5.38}$$

5.4.3 Weighting via the corrected Akaike Information Criteria

In this approach the model selection criteria AICc is used to rank the candidate models from best to worse and calculate the weight of each single model. The AICc is a bias adjusted version of the Akaike information criteria AIC. The AICc is more adapted to sample of small size. Mathematically for each of the single model the AIC criteria can be expressed as (Eq. 5.39) (Burnham and Anderson 2002; Burnham and Anderson 2004):

$$AIC = -2\log\left(\mathcal{L}(M|Data)\right) + 2K \qquad \text{Eq. 5.39}$$

where K is the number of estimated parameters in the model including the intercept and the unknown variance) and $\mathcal{L}(M|Data)$ is the likelihood of the considered model M given the data.

Assuming that the errors are normally distributed in all candidate models with a constant variance the AIC for an ordinary least square linear regression model can be computed as:

$$AIC \approx n\log\left(\frac{\sum_i^n \hat{\epsilon}_i^2}{n}\right) + 2K \qquad \text{Eq. 5.40}$$

where n is the sample size and $\hat{\epsilon}^2$ the residual sum of squares of the considered model.

According to Burnham and Anderson (2002) the Akaike Information criteria AIC does not always perform well with small sample and too many predictors. Then the AICc derived as a second order variant of the AIC is developed. In this study, the AICc was used instead of the AIC because it is more appropriate for small sample like that of the pineapple yield statistics used to train the pineapple crop models. As well, Burnham and Anderson (2002) strictly recommends the use of the AICc unless the sample size is large enough compared to the number of estimated parameters, especially when the ratio n/K is smaller than 40. The AICc can be computed as (Burnham and Anderson 2002; Burnham and Anderson 2004):

$$AIC_c = AIC + \frac{2K(K+1)}{n-k-1} \quad \text{Eq. 5.41}$$

The AICc was used to compute the Akaike weights for all candidate models and served the purpose of estimating the quantity of interest. The Akaike weights W_i for each candidate model was derived from the computed AICc as in (Burnham and Anderson 2002; Burnham and Anderson 2004):

$$W_i = \exp\left(-\frac{1}{2}(AICc_i - AICc_{min})\right) \quad \text{Eq. 5.42}$$

where $AICc_i$ is the AICc value of the considered candidate model and $AICc_{min}$ the smallest value of AICc among the values for the B candidate models.

The quantity of interest can finally be computed as (Eq.5.43):

$$E(\Delta) = \frac{\sum_{i=1}^{B} W_i \times \Delta_i}{\sum_{i=1}^{B} W_i} \quad \text{Eq. 5.43}$$

5.4.4 Weighting via Bayesian Information Criteria

The Bayesian Information Criteria is another information-based criteria used in this study. Also called Schwartz's information criteria it arises from Bayesian thoughts and assumes equal prior probability for the different candidate models and very vague priors on the estimated parameters given a model (Burnham and Anderson 2002; Burnham and Anderson 2004). It is mathematically expressed as (Ando 2010) (Eq. 5.44):

$$BIC = -2\log\big(\mathcal{L}(M|Data)\big) + K \times \log(n) \quad \text{Eq. 5.44}$$

It assumes that the errors are normally distributed in all candidate models with a constant variance. For an ordinary least square linear regression model the BIC can be re-expressed as:

$$BIC \approx n \log\left(\frac{\sum_i^n \hat{\epsilon}_i^2}{n}\right) + K \times \log(n) \qquad \text{Eq. 5.45}$$

Similar to the formula in Eq. 5.42 that gives the Akaike weights, the BIC of the candidate models is used to obtain the joint probabilities $P(M_i|D)$ of all the candidate models as in (Burnham and Anderson 2002; Burnham and Anderson 2004):

$$W_i = P(M_i|D) = \exp\left(-\frac{1}{2}(BIC_i - BIC_{min})\right) \qquad \text{Eq. 5.46}$$

The posterior probability of each candidate model is then computed by dividing the joint probability of that model by the marginal probability or normalisation constant that is the sum of the joint probabilities over all candidate models. The quantity of interest is derived with the obtained posterior probabilities W_i according to the same formula in Eq. 5.43.

5.4.5 Bayesian Model Averaging

The Bayesian approaches differ in their ways of deriving the prior probabilities or prior knowledge/beliefs on the candidate models. According to Pelenis (2014), Bayesian approaches are more effective and thus should be preferred when the sample size is small because it allows an exact inference given observed data instead of relying on asymptotic approximations. Here, the Bayesian model averaging technique called BMA is another Bayesian approach that assumes uniform priors on the candidate models and on the estimated parameters. Following this BMA approach for each model M_i the distribution of the posterior densities can be expressed as (Paeth et al 2008b; Paeth et al 2010):

$$P(M|D) = \frac{1}{B} \times \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi}\sigma} exp\left\{-\frac{\hat{\epsilon}_i^2}{2\sigma^2}\right\} \qquad \text{Eq. 5.47}$$

where $\frac{1}{B}$ stands for the prior probability on each model M_i and the rest of the equation represents the likelihood of the considered model given the observed data.

Taking the posterior probability of each model $P(M_i|D)$ as the weights W_i of the candidate models the quantity of interest can as well be obtained following Eq.5.43.

5.4.6 Automatic Bayesian Model Averaging

Another Bayesian approach used in this study is the automatic Bayesian model averaging (ABMA) for multiple linear regression models in which the candidate models have got different prior probabilities. These prior probabilities are automatically set through an appropriate choice of a hyper parameter μ that is the probability of inclusion of a potential predictor in each model. In this study this approach is applied following Liang et al (2001). Starting with a MLR model of the form of that in Eq. 5.25 a QR decomposition should first be performed on the matrix of predictors to re-parameterize this matrix in a way that the columns of the regression matrix are orthogonal. In this study, the re-parameterisation was not done as the predictors were derived from principal components analysis and thus were already orthonormal. Assume that $M_i = (M_i^1, \dots, M_i^k)$ represents a model, $M^{(p)}$ a model having p predictors and θ the set of free parameters of that model $\theta = \left(M^1, M^2, \dots, M^k, \beta_{p0}, \beta_{p1}, \dots, \beta_{pp}, \sigma^2\right) = (M^{(p)}, \beta_{pp}, \sigma^2)$. For that model the likelihood function is estimated as:

$$P\left(Y\middle|X, M^{(p)}, \beta_p, \sigma^2\right) \propto L_p\left(Y\middle|X, M^{(p)}, \beta_p, \sigma^2\right) = \frac{1}{\left(\sqrt{2\pi}\sigma\right)^n} exp\left\{-\frac{\left\|Y - X_p\beta_p\right\|^2}{2\sigma^2}\right\} \qquad \text{Eq. 5.48}$$

The prior distribution of θ combines the prior probability of the model (inclusion or not of a potential predictor in the model $M^{(p)}$), the prior probabilities of each of the partial regression parameters β_p in the model $M^{(p)}$) and the prior probability of the unknown variance σ^2. Under the assumption that all k potential predictors are linearly independent and each has a prior probability μ to be included in the model $M^{(p)}$, the prior probability of the model $M^{(p)}$ is derived as:

$$P\left(M^{(p)}\right) = \mu^p (1-\mu)^{k-p} \qquad \text{Eq. 5.49}$$

where μ is an hyper parameter to be specified later. As well further assumptions on the a priori independence of the partial regression parameters β_p and the unknown variance σ^2 allow to derive the following prior distribution for the partial regression parameters (Eq. 5.50) in each model $M^{(p)}$.

$$P\left(\beta_p\middle|M^{(p)}\right) = \frac{1}{\left(\sqrt{2\pi}\tau_p\right)^{p+1}} exp\left\{\frac{-1}{2\tau_p^2}\sum_{i=0}^{p} \beta_{pi}^2\right\} \qquad \text{Eq. 5.50}$$

The prior distribution of the unknown variance is also derived as (Eq. 5.51):

$$P\left(\sigma^2 \middle| M^{(p)}\right) = \begin{cases} \dfrac{1}{2log\left(\tau_p^2\right)} \dfrac{1}{\sigma^2} & if \ \dfrac{1}{\tau_p^2} < \sigma^2 < \tau_p^2 \, , \\ 0 & otherwise \end{cases} \qquad \text{Eq. 5.51}$$

In Eq. 5.50 and Eq. 5.51 τ_p is also a hyper parameter to be specified later.

Multiplying the likelihood (in Eq. 5.48) and the three different prior probabilities (in Eq. 5.49, Eq. 5.50, Eq. 5.51) yields the following joint distribution:

$$\begin{aligned} & P\left(M^{(p)}, \beta_p, \sigma^2 \middle| Y\right) \\ & \qquad \propto P\left(Y \middle| X, M^{(p)}, \beta_p, \sigma^2\right) \times P\left(\beta_p \middle| M^{(p)}\right) \times P\left(\sigma^2 \middle| M^{(p)}\right) \times P\left(M^{(p)}\right) \\ & \qquad = \mu^p (1-\mu)^{k-p} 2\pi^{-(n+p+1)/2} (\sigma^2)^{-(\frac{n}{2}+1)} \left[2log\left(\tau_p^2\right)\right]^{-1} \left(\tau_p^2\right)^{-(p+1)/2} \\ & \qquad\qquad exp\left\{-\frac{RSS_p}{2\sigma^2}\right\} exp\left\{-\frac{1}{2\sigma^2}\sum_{i=0}^{p}(\beta_{pi}-\hat{\beta}_{pi})^2 - \frac{1}{2\tau_p^2}\beta_{pi}^2\right\} \end{aligned} \qquad \text{Eq. 5.52}$$

Where $RSS_p = \left\|Y - X_p\hat{\beta}_p\right\|^2$ is the regression sum of square errors from the considered model $M^{(p)}$ with p variables, $\left\|Y - X_p\hat{\beta}_p\right\|^2 = RSS_p + \sum_{i=0}^{p}(\beta_{pi} - \hat{\beta}_{pi})^2$

Integrating out β_p from Eq. 5.52 and assuming that the τ_p^2's are restricted in a way that $\log\left(\tau_p^2\right)\left(\tau_p^2\right)^{(p+1)/2} = \log(\tau_0^2)(\tau_0^2)^{1/2}$ the joint probability can be re-expressed as (Eq.5.6):

$$\begin{aligned} \frac{P\left(M^{(p)} \middle| Y\right)}{P(M^{(0)}|Y)} = \left(\frac{\mu}{1-\mu}\right)^p \int_{\frac{1}{\tau_p}^2}^{\tau_p^2} \frac{1}{(\sigma^2)^{\frac{n}{2}+1}} \frac{1}{\left(\sigma^{-2}+\tau_p^{-2}\right)^{\frac{p+1}{2}}} \\ exp\left\{-\frac{RSS_p}{2\sigma^2} - \frac{1}{2\sigma^2}\frac{\tau_p^{-2}}{\sigma^{-2}+\tau_p^{-2}}\sum_{i=0}^{p}\hat{\beta}_{pi}\right\} d\sigma^2 \end{aligned} \qquad \text{Eq. 5.53}$$

where $M^{(0)}$ represents the null model.

Considering $P\left(M^{(0)} \middle| Y\right)$ as a constant in the derivation of Eq. 5.53 and assuming that τ_0^2 converges to infinity the logarithm of the joint distribution (up to an additive constant) can finally be derived as (Eq.5.54) (Liang et al 2001):

$$\begin{aligned} \log P\left(M^{(p)} \middle| Y\right) = \mathrm{p} \log\left(\frac{\mu}{1-\mu}\right) + \frac{n-p-1}{2}\log 2 - \frac{n-p-1}{2}\log\left(RSS_p\right) \\ + \log\Gamma\left(\frac{n-p-1}{2}\right) \end{aligned} \qquad \text{Eq. 5.54}$$

In this later equation the only parameter to be specified is μ.

In the ABMA approach, the hyper parameter μ is automatically set as follows:

$$\mu = 1/[1 + \hat{\sigma}_k \exp(1 + 1/(2(n-1)))] \qquad \text{Eq. 5.55}$$

where $\hat{\sigma}_k$ stands for an estimator of μ from the full model (the model with all k potential predictors). It is estimated as:

$$\hat{\sigma}_k = \sqrt{RSS_k/(n-k-1)} \qquad \text{Eq. 5.56}$$

The posterior probability of a given model is finally obtained by dividing the joint probability of that model by the marginal probability that is the sum of the joint probability over all considered models. Then the quantity of interest is once more derived following Eq.5.43 taken the posterior probabilities $P\left(M^{(p)}\middle|Y\right)$ as the weights. Further details about the ABMA method can be found in Liang et al (2001).

5.5 Goodness-of-fit assessment

The performance of each single model and of the combined model was evaluated with respect to the coefficient of determination, the root mean square error and the Brier skill score.

The coefficient of determination (R^2) describes the linear dependency between measured and simulated values during the reference period. It lies within the range of 0 and 1 and is calculated following Eq. 5.36.

The root mean square error (RMSE) is another goodness-of-fit coefficient. It expresses the average prediction errors of a model. Thus values close to 0 indicate a model of good performance. The RMSE formula can be written as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\tilde{Y}_i - Y_i\right)^2} \qquad \text{Eq. 5.57}$$

where Y and $\tilde{Y}$ denote respectively the observed yield data and the simulated yield data during the reference time period P1.

The Brier skill score (BSS) is another goodness-of-fit coefficient used here. The BSS is a measure of the increase in explained variance by a model with respect to the predicted mean over the reference period or the climatological forecast (Paeth et al 2006). It is expressed as (Von Storch and Zwiers 2004; Paeth et al 2006; Roulston 2007; Paeth et al 2010):

$$BSS = 1 - \sqrt{\frac{\sum_{i=1}^{n}\left(\tilde{Y}_i - Y_i\right)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \qquad \text{Eq. 5.58}$$

A perfect deterministic prediction is indicated by BSS = 1.0 while prediction no better than the reference has BSS = 0.0. In general, positive values of BSS reflect a good prediction skill compared with the observed mean over the reference period P1, while negative values of BSS reflect no added values (Roulston 2007; Paeth et al 2010).

6 EVALUATION OF THE DEVELOPED STATISTICAL CROP MODEL FOR PINEAPPLE

In this Chapter the leading spatial modes of variability for precipitation and mean air temperature in the north hemispheric part of Africa (0° – 40°N/ 20°W– 40°E) are presented together with their annual temporal evolution. Their analysis focuses more on the patterns in tropical West Africa. Besides, potential climate predictors for the developed pineapple yield projection models in the Republic of Benin are shown as well as the selection of the climate predictors in the modelling systems. Finally the models are evaluated with respect to the historical yields in the reference period and the multi-model averaging techniques applied are compared.

6.1 Leading patterns of precipitation and mean air temperature variability in West Africa

The crop models developed is this study are PCs-based multiple linear regression models. Thus as explained in the previous Chapter (sub-chapter 5.2) principal components analysis was performed on the covariance matrix of deseasonalised monthly time series of precipitation and mean air temperature. Before using the obtained PCs for prediction, it is common practice to make sure that the leading PCs and their associated modes of variability that explained as much as possible variance are linked to physical processes. In this study this evaluation was done for only the leading two EOFs patterns of precipitation and mean air temperature, and their associated PCs. Figures 6.1 and 6.2 respectively present those leading two EOFS and PCs for annual precipitation and annual mean air temperature over north of Africa (0°N-40°N/20°W-40°E).

In Figure 6.1 the first EOF pattern explained about 8.4% of the total variance of precipitation in the study domain while the second EOF pattern holds just about 5.8% of information. Knowing that there exists strong temporal and spatial variability in precipitation over Western Africa the shares of information held by those two leading EOFs of precipitation are already important in this region. The first EOF pattern of precipitation shows a south-north decreasing gradient of precipitation. Thus it rains more in the Guinean region and the precipitation gradient decreases from the Guinean coast to the Sudanian domain and continues toward the inner Sahel. As well this first EOF pattern reproduces also the decreasing gradient of precipitation from the West toward the East. The associated PC 1 time series show large multi-decadal variability of precipitation. As presented these time series have been standardised relative to the 1961-90 and then 9-year' low-pass filters are applied. The observed PC1 - CRU time series reproduce well the relatively good rainfall conditions during the decades 1920s and 1930s in West Africa as well as the drier conditions during 1910s and 1940s. The decade 1950s seems to be the wettest on record in West Africa during the twentieth century. More extreme fluctuations are observed in the second half of the 20^{th} century. In fact, a prominent decrease in precipitation is seen during the decades 1970s and 1980s, with the most intense drought in the early 1980s followed by a slight recovery after 1990. These findings are in good agreement with those of many scholarly published work on precipitation variability in the study domain (Hulme 1992; Nicholson 1993; Nicholson 1994; Hulme 1996; Nicholson et al 2000; Nicholson 2001). The PC 1 thus represents the well-documented prolonged climatic drought that occurred over the whole sub-Saharan West Africa mainly during the second-half of the twentieth century (Nicholson et al 2000; Nicholson 2001; L'HÔTE et al 2002; Nicholson 2013).

The three PC1 - REMO reveal that in present-day REMO RCM simulations do not reproduce the observed year-to-year precipitation variability. Thus while using REMO RCM outputs emphasis should be put on the climatology instead of the annual variability. These PC1-REMO time series show also a decreasing trend in precipitation during the first-half of the twenty-first century with the highest decrease obtained under the medium greenhouse emission scenario A1B combined with land degradation REMO A1B (GHG+LCC) and the lowest decrease is obtained for REMO A1B (GHG only). Although the SRES B1 is low emission scenario compared to SRES A1B the decreasing trend in precipitation in the future obtained for PC1-REMO B1 (GHG+LCC) is much more strong than that of PC1-REMO A1B (GHG only). In fact, the changes in precipitation are not too much pronounced under the SRES A1B (GHG only). Comparison of PC1-REMO A1B (GHG only) with PC1-REMO A1B (GHG+LCC) that differs by only the LCC implemented in the latter one demonstrates the sensitivity of West African precipitation to changes of the land surface conditions. It shows that higher decrease in precipitation in the future is obtained when future land degradation scenario is taken into account. In fact, in general higher negative trends in the future are observed for the REMO simulations that combined land degradation (LCC). Thus land degradation might induce more reduction in precipitation in tropical West Africa than greenhouse gases emission. This reveals the major role rapid deforestation and overgrazing can play in the reduction of precipitation in tropical West Africa.

The EOF 2 pattern of precipitation shows an opposing spatial tendency in precipitation distribution between the Guinean part and the Sahelian part of West Africa. The Guinean region is wet while the Sahelian region is dry. When associated with the PC 2 – CRU it reveals that the drought tendency over tropical West Africa has started in the 1980's in the Guinean part while since the 1970's the Sahelian part was already drying (Le Barbé et al 2002). The decreasing trends of precipitation in the future shown in the PC1-REMOs are still quite well noticeable in the PC2-REMOs.

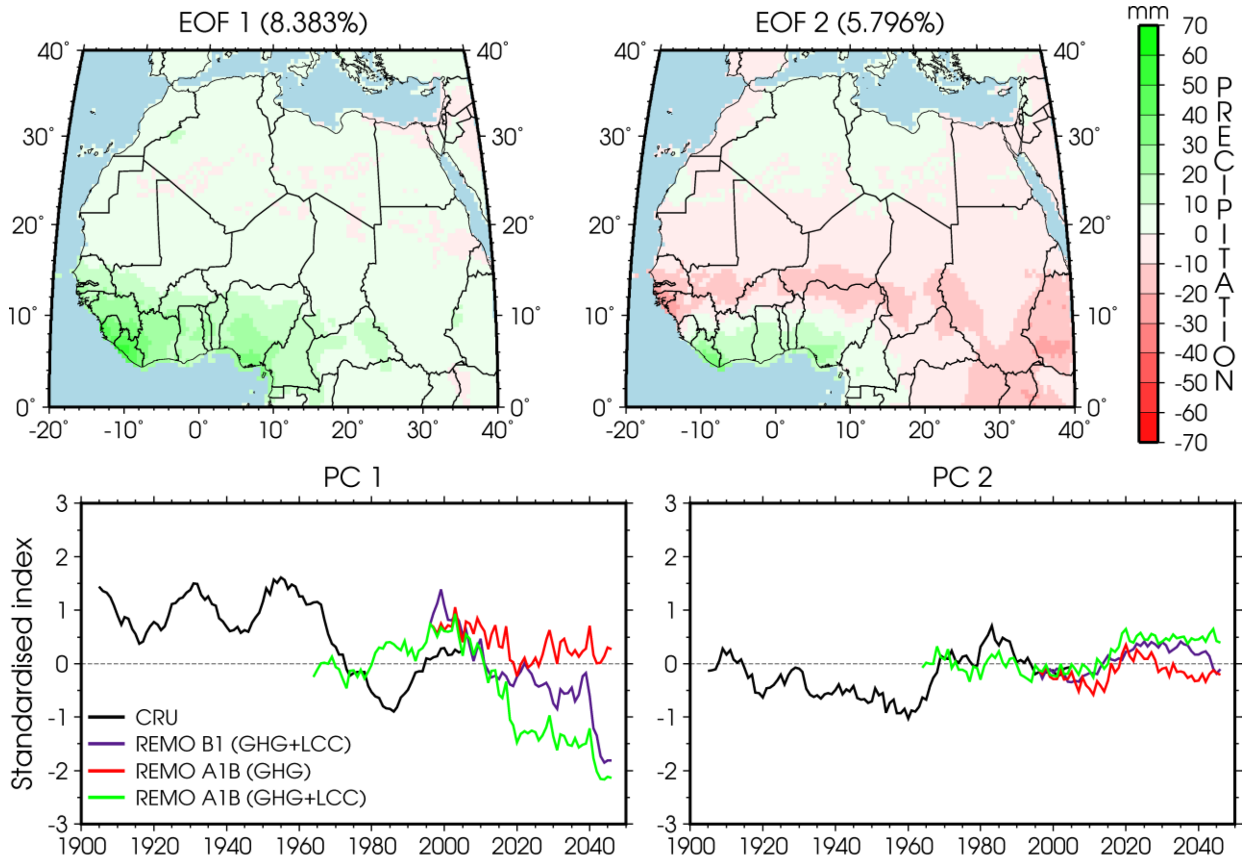


Figure 6.1: 9-year's low-pass filtered time series of the leading two principal components of annual precipitation sums from CRU and REMO, and their associated spatial patterns.

The PCs are expressed as standardised anomalies relative to 1961-1990 climatology.

For mean air temperature in Figure 6.2 the EOF1 pattern shows a more or less homogenous pattern of warming with the mean air temperature increasing gradually from the Coast to the continent (from west to east and from the Guinean coast to the inner Sahel and the Sahara). The EOF 1 pattern is representative of a dominant warming through the twentieth century. Associated to that pattern the PC1 – CRU shows below normal temperature before the year 1930 and above normal temperature between 1930 and early in the decade 1940s. As well one can see that the mean air temperature variation is more or less stable and cooler than normal from around 1945 to 1980. This cooling might be due to the radiative effect of sulphate aerosols concentrations in the atmosphere. According to Hulme et al (2001) sulphate aerosols – derived from sulphur dioxide emissions to the atmosphere – reflect back the solar radiation and this can directly have a cooling effect on the climate. As well, sulphate aerosols can also indirectly induce cooling of the atmosphere by changing the reflectivity and longevity of cloud (Schimel et al 1996; Hulme et al 2001). From the middle of the decade 1970s a steady increase of the mean air temperature is noticeable in PC1 – CRU, with an acceleration since 1990's. This increase of the temperature is likely related to more CO_2 emissions as a result of anthropogenic activities together with other greenhouse gases which also act to warm the atmosphere. In present-day the REMO simulations for mean air temperature reproduce quite well the observed mean climatology and variability. In general the trends obtained in PC1-CRU and the PC1-REMOs during the twentieth century are in line with the year-to-year variations of the global land surface temperature. Hulme et al (2001) state that the warming of the decades 1910s to 1930s and that of the post-1970's occur simultaneously in Africa and worldwide.

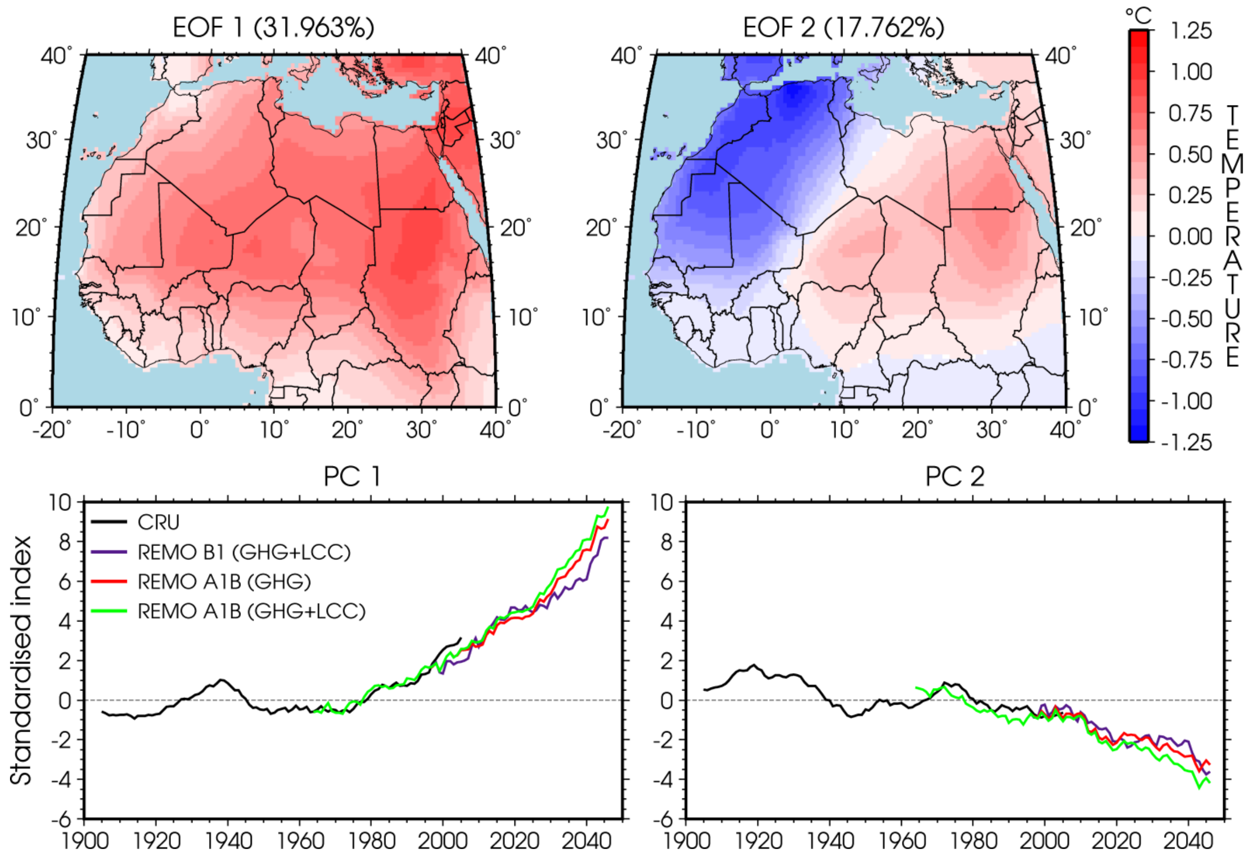


Figure 6.2: 9-year's low-pass filtered time series of the leading two principal components of annual mean near-surface air temperature from CRU and REMO, and their associated spatial patterns.

The REMO simulations confirm the long-term positive anomalies of the mean air temperature observed since the middle of the decade 1970s and even more those PC1-REMO show an enhancement of the warming signal during the first-half of the twenty-first century. The strongest temperature increase is obtained under the combined scenario A1B (GHG+LCC).

Unlike the first mode, the second mode (EOF 2 pattern) of mean air temperature variability is expressed as a dipole with opposite loadings over northwest and northeast Africa. The change occurs across a diagonal passing more or less along the border shared by Niger and Algeria. Similar spatial structure in northern hemispheric Africa was reported by Collins (2011) for the December-February season while analysing mean near-surface air temperatures using the mean total lower-tropospheric temperature anomalies between 1979-1994 and 1995-2010 with El Niño and La Niña events removed so that only neutral ENSO years are considered. But she concluded that the localized temperature reduction centered on Egypt was not statistically significant at a 5% level. Although the variability in the PC 1 are removed before deriving the PC2s (i.e. PC 1 and PC 2 are orthonormal), when inversed according to the sign of the dominant loadings in EOF 2 over West Africa, the PC 2-REMOs still display the dominant positive trend (strong warming signal) in mean air temperature until 2050.

6.2 Selection of potential climate predictors for simulating pineapple yield

The selection of the potential climate predictors for the pineapple crop models are based on linear correlation of the available historical records of pineapple yield with the overlapping time series of the first 20 PCs of mean air temperature and precipitation for each month in the idealised crop calendar defined in Chapter 4. The outcomes of the correlation analysis pertinent for pineapple production are presented in Table 6.1. It should be noted that pineapple is a perennial crop that is grown over two calendar years.

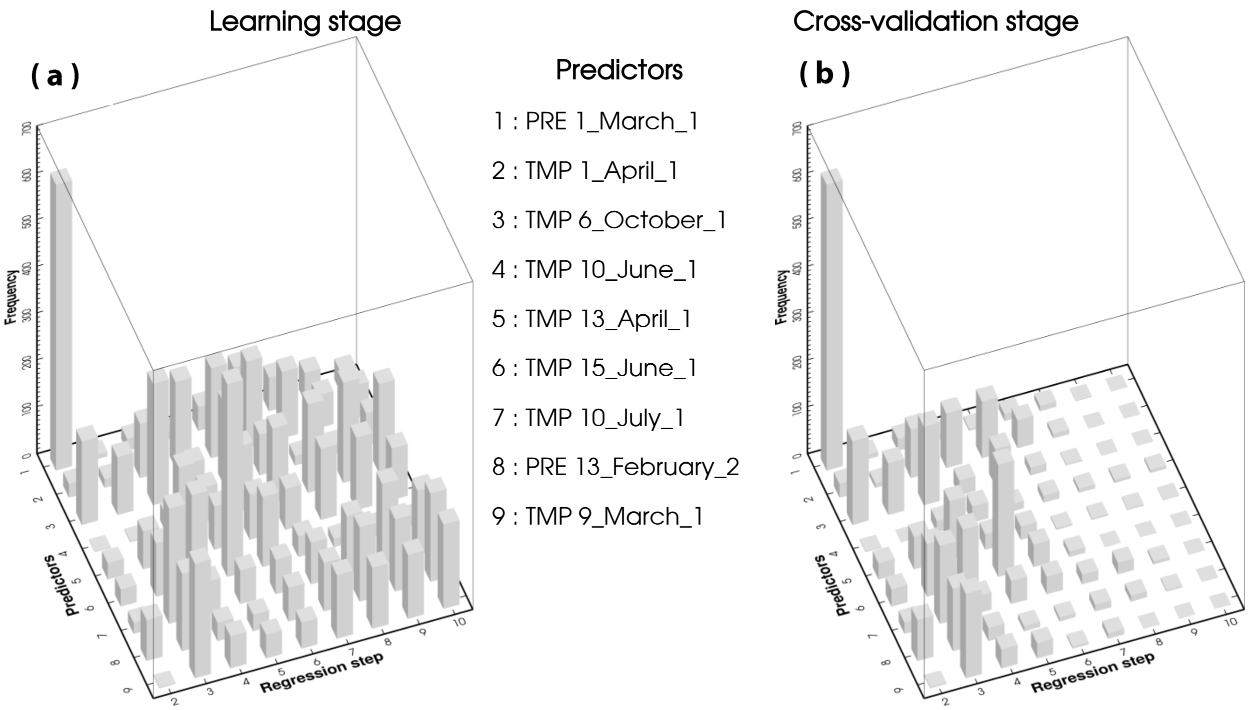
Table 6.1: Correlation coefficients of the climate predictors for the pineapple crop model.

Predictors	Pearson correlation coefficient (r)
PRE_1_March_1	+0.86
TMP 9_March_1	-0.74
TMP 1_April_1	-0.71
TMP 13_April_1	+0.78
TMP 6_October_1	-0.79
TMP 10_June_1	+0.72

TMP 15_June_1	+0.72
TMP 10_July_1	+0.76
PRE 13_February_2	+0.78

In fact the potential predictors are those statistically significant at 1% and with $|r| \geq 0.7$. Amongst the 9 selected potential climate predictors only 2 predictors are related to precipitation. These are the 1st PC of precipitation in March of the 1st calendar year (PRE_1_March_1) and the 13th PC of precipitation in February of the 2nd calendar year (PRE_13_February_2). In southern Benin where pineapple is grown February and March are known to be dry months but March is a little bit wetter as the first regular rainfall events of the first rainy season along the Guinean Coast occur around mid-March. Hence March corresponds more or less to the onset of the first rainy season along the Guinean Coast and thus in southern Benin. As the sign of the linear correlation coefficients for the two precipitation-related predictors is positive it is expected that any increase (decrease) in precipitation in these 2 months will increase (decrease) pineapple yield. The positive sign of the partial regression parameter associated to those predictors largely confirm this expectation. For temperature the potential predictors were all selected for only the first calendar year. As well, the correlation analysis revealed that mean air temperature is more important for pineapple production in five months (March, April, June, July and October). While taken into account both the sign of the correlation coefficients of each predictor and that of the loadings of the corresponding EOF pattern over Benin (confer. Appendix B) negative effects are expected from any increase in mean air temperature in March (TMP 9_March_1), April (TMP 1_April_1 and TMP 13_April_1), June (TMP 15_June_1), and October (TMP 6_October_1). Meanwhile positive effects on pineapple yield are expected from increase in mean air temperature in June (TMP 10_June_1) and July (TMP 10_July_1). Here it is seen that for June the two temperature-related predictors (TMP 10_June_1, TMP 15_June_1) display contrary effects. This is due to the fact that they have opposite signs in their respective EOF loadings over Benin. In general opposing effects on the yield are expected for some of the predictors. Therefore the resulting impacts of the combination of all these predictors on the yield depend on the importance of the predictors as selected in the cross-validated multiple linear regressions system. Figure 6.3 presents the selection of the predictors in the statistical crop model. It has to be kept in mind that 1000 iterations were run and therefore the developed crop model combines the outputs of all these iterations.

Figures 6.3 a,b show how often each predictor is selected at the consecutive regression steps without cross-validation and after cross-validation. From Figure 6.3b one can see that the cross-validation procedure has helped to reduce the dimensionality of some individual models and thus to avoid overfitting of those models. It also shows that the predictor PRE 1_March_1 was the most selected at the 2nd regression step (1st regression step being for the intercept), followed successively per order of importance by TMP 9_March_1, TMP 6_October_1, TMP 15_June_1 and TMP 1_April_1 at the subsequent regression steps. Here the importance of a predictor is dictated by how often it is chosen within 1000 iterations. Regardless of the regression step at which a given predictor is taken, Figure 6.3c displays another picture with still PRE 1_March_1 as most chosen predictor, but followed per order of importance by TMP 6_October_1, TMP_15_June_1, TMP 1_April_1, TMP 10_July_1, TMP 13_April_1 and others. Meanwhile Figure 6.3d shows that most models included 4 predictors or even only one predictor. In fact from the 4 figures combined in Figure 6.3 it is not easy to decide on the dimensionality of a relevant model and state what the relevant predictors are. This has motivated the combination of the outcomes of the 1000 iterations (i.e. ensemble averaging) instead of relying on a single "best" model and drawing inferences from it as if it is "true" (Liang et al 2001). Hence inferences are made on uncertainties associated with the partial regression parameters estimations, the dimensionality of the models, and the quantity of interests in the model space.



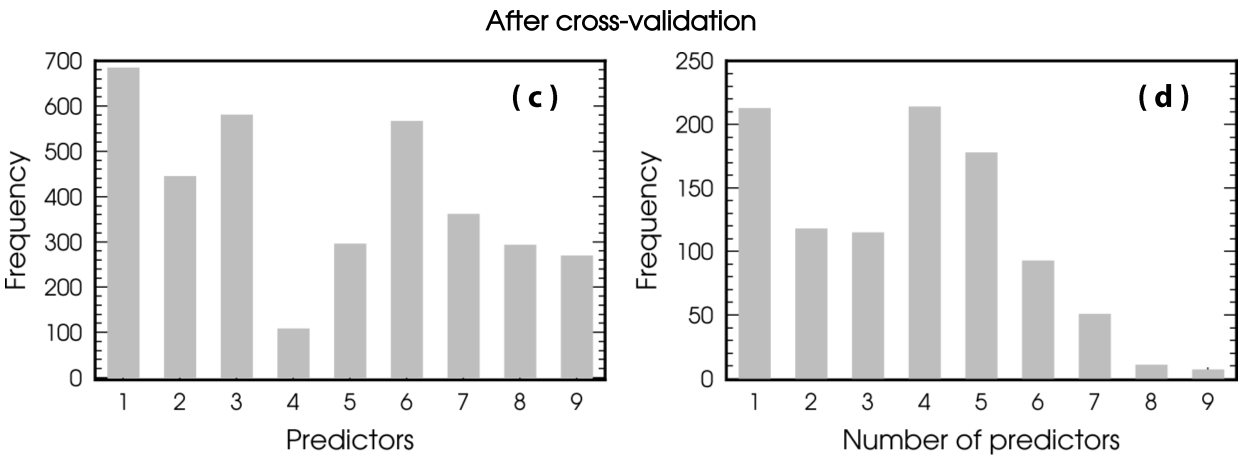


Figure 6.3: Selection of the predictors in the statistical pineapple crop models. The frequencies indicate the number of times a given predictor or a given number of predictors is selected out of the 1000 iterations used in the model development.

Table 6.2 presents per order of importance the 10 models (i.e. predictors included in those 10 models) having the highest posterior probabilities with respect to the ABMA method. As well it highlights the most weighted model following other weighting methods applied, and the similarities of those methods in selecting some leading models.

Table 6.2: Ten highest weighted / posterior pineapple crop models resulting from the ABMA method.

No.	Prob. (%)	Included predictors							
1 **a c e**	2.282	1	2	3	4	5	6	7	
2 a c e	2.145	1	2	3	4	5	6	7	8
3 a c e	2.145	1	2	3	4	5	6	7	8
4 a **b** c **d** e	1.396		2	3			6	7	
5 e	1.163	1	2	3			6	7	8
6 e	1.118	1	2	3			6	7	8
7 b c d e	1.107		2	3			6	7	
8 a b c d e	1.059		2	3			6	7	
9 a b c d e	1.059		2	3			6	7	
10 e	1.053		2	3			6	7	8

The probability is expressed as a percentage. The letters a b c d e stand respectively for the adjusted R square, Akaike weights with AICc, BIC, BMA and ABMA multi-model methods. The bold letters indicate the model with the highest weight/posterior following each of the aforementioned weighting method. The reader should refer to Figure 6.3 for the meaning of the number assigned to each predictor.

Whatever the ensemble-averaging methods the predictor TMP 9_March_1 (predictor 9) is not selected in any of the leading 10 models. In fact, all potential predictors were added step by step in the multivariate linear regressions system and after cross-validation some of them were dropped. Meanwhile the predictors TMP 1_April_1, TMP_6_October_1, TMP 15_June_1, and TMP 10_July_1 (predictors 2, 3, 6, 7) appeared to be quite important as they are always included in the most weighted models.

6.3 Performance of the pineapple crop model and selection of multi-model averaging methods

Before relying on any model it is paramount to assess the performance of the model, as model prediction cannot be credible if the model is not able to skilfully reproduces the observations over the reference period. In this thesis the performance of the individual pineapple crop models and that of the combined model are evaluated by means of their computed R square, RMSE and BSS. For the individual models the R square range between 0.74 and 0.99, with the median around 0.93 and the lower 25% tail and the upper 25% tail of the models respectively below 0.83 and above 0.97. Thus, high amounts of the variability in the observed yields are reproduced by the variability of the predictors. Similarly the Brier-skill-score (BSS) also show that in general the individual models fit quite well the observations, i.e. good reproduction of the mean and the year-to-year variations in the reference period. In fact, the BSS of the individual models range from 0.41 to 0.93 (lower 25-percentile tail ≤ 0.57; median ≈ 0.72; and higher 25-percentile tail ≥ 0.83).

The individual crop models were averaged following different weighting methods explained in the previous Chapter (section 5.4). Figure 6.4 and Figure 6.5 display respectively the R square and the BSS of the combined crop model following those methods, and the probability distribution of the simulated average yield over the reference period.

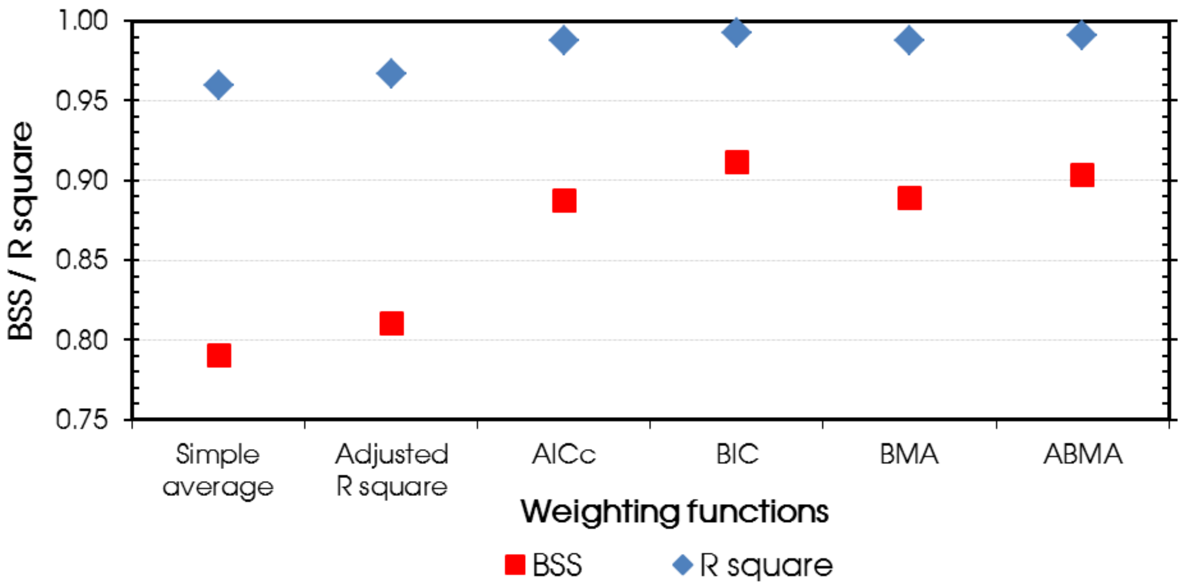


Figure 6.4 : Performance of the combined model following different multi-model averaging methods.

As shown by Figure 6.4 the combined model is more robust than the individual models. Whatever the weighting methods the R square of the combined model is higher than 0.95. Thus almost all the variability (at least 95%) in the pineapple yield is climate-related. Further, the figure shows two groups of multi-model performance: the frequentist approaches (weighting based on simple average and adjusted R square) with both their R square and BSS clearly below those of the information-based criteria (AICc, BIC, BMA and ABMA). Comparing the four latter criteria that are well rooted in the Bayesian framework, more robust predictive performance are obtained with the BIC and the ABMA. But the ABMA method has been preferred because contrary to the BIC method that assumes very vague priors on the partial regression parameters given a model and equal probability on the models the ABMA method automatically sets different prior probabilities on the models in the model space and different priori distributions on each of the model parameters within each model.

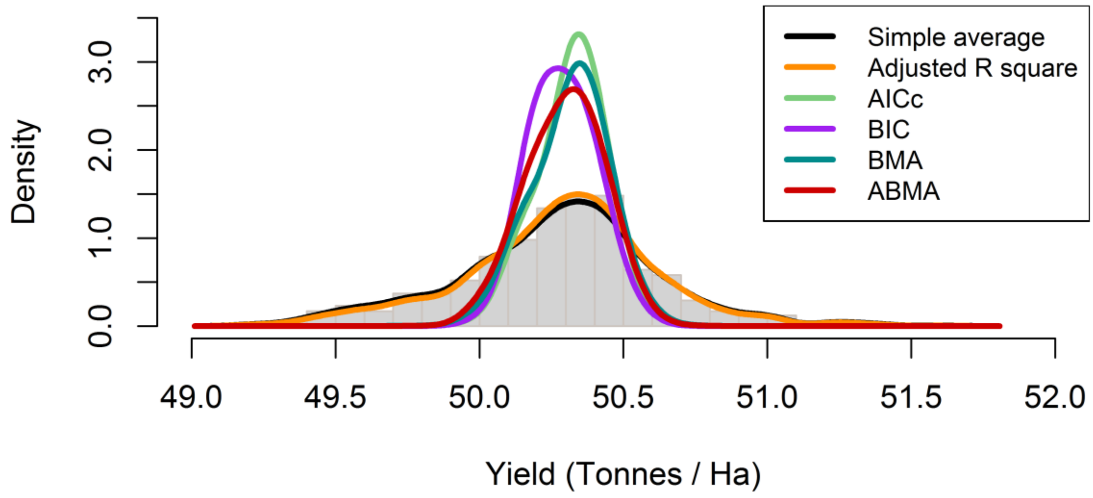


Figure 6.5 : Probability distribution of the simulated average yield over the reference period following different multi-model averaging methods.

Figure 6.5 shows the uncertainty in predicting the average yield over the reference period. Over that time period (crop production years 1995/96 to 2008/09) the observed average yield amounts to 50274.72 Kg/Ha. In Figure 6.5 the centre of the curve of a probability distribution function describes the expected value whereas the width of the curve describes the uncertainty surrounding the estimation. Whatever the weighting methods high reliability is obtained as the expected value is always close to the observed mean (i.e. small conditional bias). But poor resolution and low sharpness (i.e. larger estimation standard errors) are observed with the frequentist approaches (simple average, adjusted R square) whereas high resolution and high sharpness are obtained with the Bayesian methods. Comparison of the four Bayesian methods reflects the sensitivity of the posterior model probabilities to the specification of the prior distributions.

7 MODELLING PINEAPPLE YIELD IN BENIN UNDER FUTURE CLIMATE CHANGE CONDITIONS

This Chapter presents the present-day and future evolution of the climate predictors time series relevant for the prediction of pineapple yield changes in the Republic of Benin. The developed pineapple crop model was forced with present-day and future climate predictors statistically derived from REMO RCM transient simulations over north hemispheric Africa, under different combinations of future climate change and land degradation scenarios. The resulting projections of pineapple yield changes under the various scenarios are shown. As well the contribution of the different/groups of climate predictors to the elaborated yield is quantified.

7.1 Temporal evolution of the climate predictors for pineapple production in the future

For the transferability of the pineapple crop model developed and evaluated in the previous Chapters (Chapters 5 and 6) to REMO RCM, relevant climate predictors derived from REMO RCM simulations over the study domain were needed. Figure 7.1 displays the present-day and future time series of those climate predictors. As shown for each predictor the data are standardised relative to the climate normal period 1961-1990 using averages and variances of the relevant PCs over all months in that time period. The interpretation of those data is done here in light of the associated spatial modes of variability over the republic of Benin (see Appendices A & B for the EOFs pattern). In Figure 7.1 low rainfall amounts are obtained in February and March. Whatever the emission scenario considered, there is nearly no deterministic trend for the predictor related to precipitation in March of the first calendar year (PRE 1_March) whereas a slight positive trend is obtained for precipitation in February of the second calendar year (PRE 13_February). As introduced in the previous Chapter (section 6.2) February and March are known to be in the West African dry-season which corresponds to the boreal winter. Hence during those months precipitation is rare throughout the Guineo-Sudanian zone of West Africa (Knippertz and Fink 2008). Knippertz and Fink (2008) proposed a mechanism explaining the moisture transport and the generation of rare rainfall events that are observed in the dry-season in tropical West Africa. According to those scholars boreal wintertime precipitation in tropical West Africa is closely link to a large-scale synoptic evolution in the extratropics. The underlying mechanism is characterised over tropical West Africa by two consecutive phases namely the tropical plume phase and the dynamical phase. As revealed by these authors two upper-level troughs penetrate from the extratropics into low latitudes and support both diabatic and dynamical falling of surface pressure over West Africa.

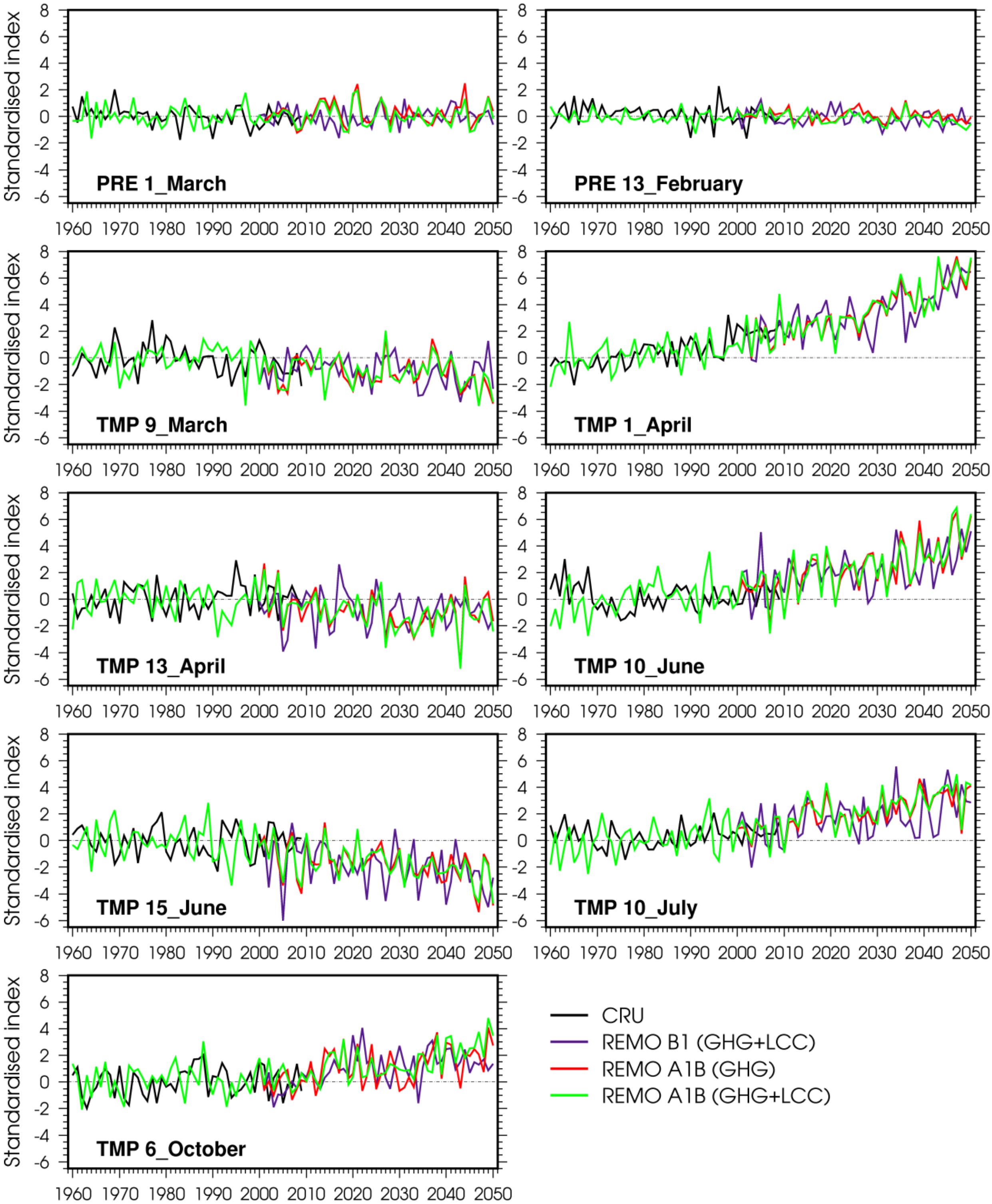


Figure 7.1: Time series of present-day and future climate predictors for pineapple production in Benin.

The data are presented as standardised anomalies relative to the climate normal period 1961-1990.

First, diabatically the fall of surface pressure is induced through an anomalous radiative warming under a diagonal tropical plume on the eastern flank of a weak and quasi-stationary extratropical disturbance (first upper-level trough) (Knippertz and Martin 2005; Knippertz et al 2008). Next, dynamically surface pressure fall originates from a subsidence and warm advection associated with a second upper-level trough that intrudes into Algeria from the western Mediterranean Sea (Knippertz and Fink 2008; Knippertz and Fink 2009). Knippertz and Fink (2009) argued that the latter mechanism related to warm advection is statistically more important than the previous one. In response to those falls of surface pressure, moist low-level monsoon air from the Gulf of Guinea flows into the continent till the Sudanian zone (9-12°N). It induces the formation of deep moist convection and thus the development of rainfalls in the Guineo-Sudanian zone (Knippertz and Fink 2008; Knippertz and Fink 2009).

In contrast to the two dry-season precipitation related predictors net year-to-year variations are seen for the mean temperature related predictors. Compared to the 1960-2000 period these variations are bigger during the first-half of the 21st century. These mean temperature related predictors display all a positive trend in both the present-day and future. The highest increases in the future are observed for the predictors related to temperature in April and June (TMP 1_April and TMP 10_June). The increase in the future amounts up to 7 times the standard deviation in the climatological normal period 1961-1990.

Comparison of low-pass filtered time series of the temperature related predictors (not shown) under the three GHG emission scenarios reveals that the temperature increase in the future is higher under both the scenarios A1B only and A1B+LCC than under the B1+LCC combined scenarios. As well, while considering only the A1B and A1B+LCC scenarios it is seen that the future temporal evolutions of the predictors under those two scenarios are close, implying minor effects of land degradation on mean near-surface air temperature variations in the future during those months important for the prediction of pineapple production.

7.2 Projection of pineapple yield changes under future climate change conditions

Assuming that the statistical transfer functions developed for the pineapple crop model are stationary in time the crop model developed with CRU predictors was transferred to the REMO RCM simulations by forcing this model with the REMO predictors in Figure 7.1. Figure 7.2 presents, for different multi-model averaging methods, the present-day and future temporal evolutions of pineapple yield changes under SRES A1B+LCC scenarios. This Figure displays in present-day (1960-2000) year-to-year fluctuations of the pineapple yield variations between 2.7% increase and 2.5% decrease relative the average pineapple yield over the crop production years 1995/96 through 2008/09. From 2001 a trend toward a decrease of the yield is observed. While using a simple average method to combine the outputs of the 1000 iterations it is seen that a decrease of the pineapple yield up to -5.7% will be attained by the middle of the 21[st] century (2050). In a similar way the multi-model combination via adjusted R square shows that by 2050 up to -6.3% yield changes should be expected. Contrary to the two previous multi-model combination methods the Bayesian methods indicates that more yield reduction are to be expected in 2050. As a result of different specifications of the prior settings (confer section 5.4) the future pineapple yield expectations vary slightly across the Bayesian methods followed for multi-model combination. Around -9.2%, -10.9%, -11.9 % and -12% yield changes will be obtained by 2050, respectively with the multi-model averaging via BIC, ABMA, BMA and Akaike weights (weighting with the AICc). This reflects the sensitivity of the yield projection to the multi-model combination techniques applied and thus addresses one source of uncertainty in crop yield projection, the one related to the structure of the crop model itself.

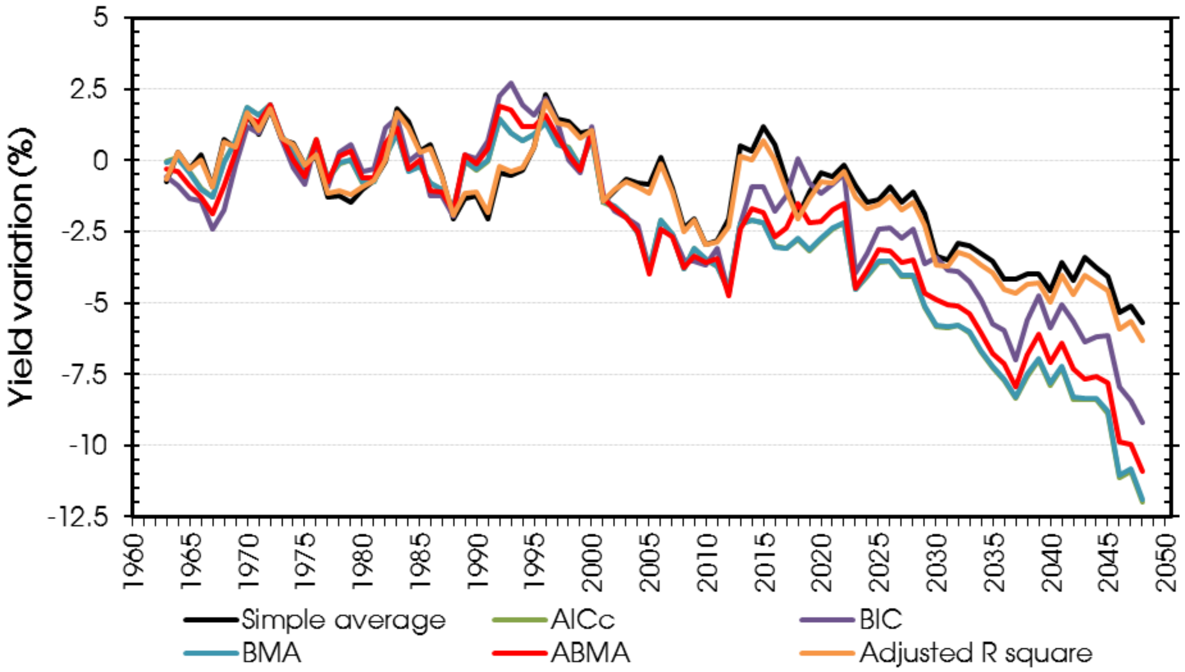


Figure 7.2: Five years-filtered time series of future pineapple yield changes in Benin under SRES A1B+LCC combined scenarios, and according to different multi-model averaging techniques.

In fact, model estimates are not the absolute answers. Hence it is generally preferable to provide estimated averages together with confidence interval estimates (Wang et al 2005). In addition, there are uncertainties in the driven-climate data. To provide robust crop yield projections the crop model should be forced with future climate data under different greenhouse gas emission scenarios as the future climate is itself uncertain.

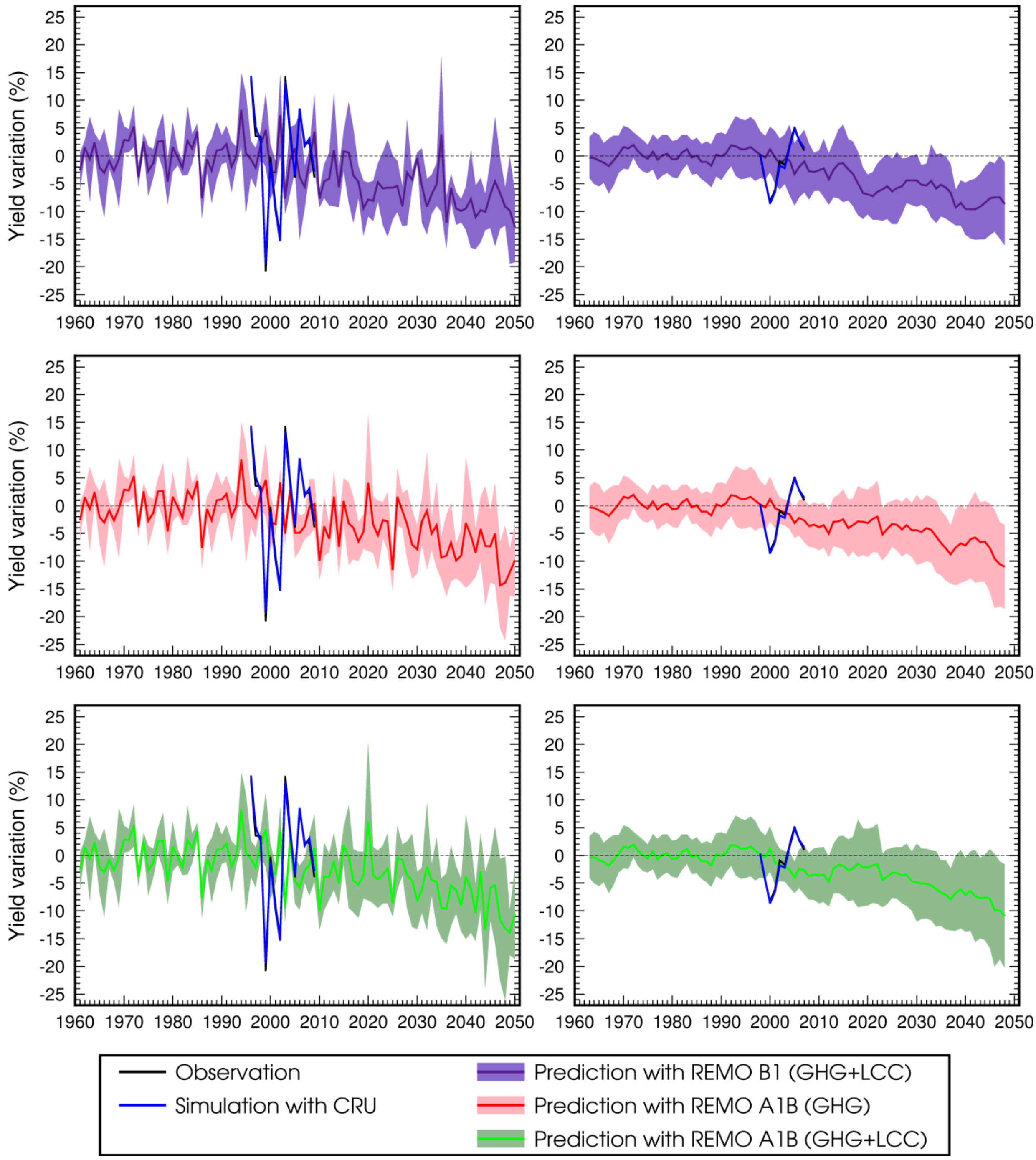


Figure 7.3: Historic and future pineapple yield change in Benin under different climate change scenarios

The yield changes are computed relative to the average yield over the crop production years 1995/96 to 2008/09. The left and the right hand-sides of the figure display respectively the unfiltered and the five-years low-pass filtered time series .

Figure 7.3 shows present-day and future pineapple yield changes, and their confidence interval estimates under three different GHG emission scenarios representing various levels of future human interference with the climate. For all crops the yield changes were computed relative to the average yield of the given crop over the production years 1995/96 to 2008/2009. The ABMA method was used for ensemble-averaging as it was found to be the most relevant for combining the 1000 iterated pineapple yield estimations per time step (confer section 6.3). It can be seen from Figure 7.3 that whatever the emission scenarios considered there is a clear tendency towards a reduction in future yields of pineapple. Under the combined SRES A1B+LCC scenarios the yield is changing at the rate of approximately -1.53% in 10 years during the first-half of the 21st century and will go down up to around -11% by 2050. Meanwhile under the SRES A1B only and B1+LCC scenarios respectively reduction trends of about -1.49% and -1.68% in 10 years during the same time frame are obtained and by 2050 the yield variation relative to the defined reference will reach around -8.64% and -11.03% respectively. Thus, the yield predictions under the three emission scenarios are fairly similar, with the outcomes under SRES A1B only and A1B+LCC being much closer.

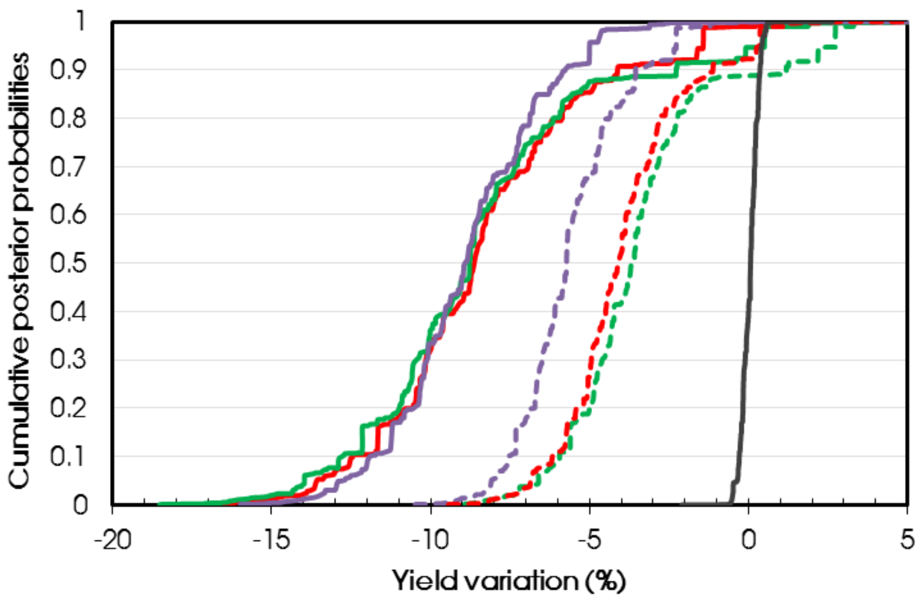


Figure 7.4: Empirical probabilistic estimation of the range of pineapple yield changes in Benin by 2025 and 2045 under future climate change.

The grey solid line shows the uncertainty associated with the reproduction of the historical pineapple yield during the crop production years 1995/96 to 2008/09. The changes are expressed relative to the average yield over the aforementioned time period. Other solid lines represent the time period 2045 (2037-2050) whereas the dashed lines represent the time period 2025 (2017-2030). The purple, red and green lines stand respectively for the yield prediction outcomes with REMO B1+LCC scenarios, REMO A1B only, and REMO A1B+LCC scenarios.

The 95% confidence intervals derived from the 1000 estimates of the yield changes at each time step show broader dispersion of the individual model estimates around the multi-model mean by 2050 compared to present-day. Hence there is more uncertainty in predicting future yield changes than reproducing historic yields. From the 95% confidence intervals there is a good reason to believe that the yield change by 2050 will be in the range of about -1.6% to -20.2% reduction. But the confidence interval does not tell us the probability that the occurring change is in that range.

For a probabilistic estimation of the range of the yield changes Figure 7.4 shows the probability level associated with the future yield changes either greater than or less than a specific value. It indicates that by around 2025 (2017-2030) there are good chances (90% probability) that the yield change will be in the range of -2.27% to -8.1%, +0.35% to -6.86%, and +2.73% to -6.61% respectively under the SRES B1+LCC, A1B only and A1B+LCC scenarios. The above 90% credible intervals are defined in such a way that the probability of being above a specified interval equals the probability of being below it. It is also seen that the yield decrease by 2025 (2017-2030) is likely to be a little bit higher (approximately 1.2 – 2% more reduction) with the SRES B1+LCC scenarios compared to the two other scenarios. As well one can see that by 2045 (2037-2050) the projections for the three GHG emission scenarios are quite similar. Again, there is a 90% chance that by 2045 the pineapple yields in Benin will vary in the intervals -1.42% to -13.6%, and +0.5% to -13.96% respectively under SRES A1B only and SRES A1B+LCC scenarios. Meanwhile under the SRES B1+LCC combined scenario the yield changes will range between -5 % and -12.7%. Thus, by the end of the first-half of this century almost the double of the decrease to be experienced by 2025 is to be expected.

The contribution of the on-going land degradation processes to the future changes in pineapple yield is assessed through comparison of the yield predictions under the SRES A1B only and A1B+LCC scenarios (Figures 7.3 and 7.4). This comparison reveals that there is merely no difference between the yield prediction under those two GHG emission scenarios. This implies that land degradation cannot be held responsible of any future pineapple yield reduction in Benin.

7.3 Separating the effects of future precipitation and temperature changes on pineapple production

From section 6.2 of the previous Chapter the most important climate predictors for the forecasting of pineapple yield in Benin are known. These predictors are related to mean near-surface air temperature and precipitation. Their temporal evolution in present-day and during the first-half of the 21st century was presented in section 7.1 according to REMO RCM simulations under different future climate change conditions. It is now important to make clear in which direction and to what extent the future variations of each of the climate predictors will affect the overall pineapple yield changes by 2050. Figure 7.5 displays the contribution of each of the climate predictors to the elaborated yield under the SRES A1B+LCC scenarios.

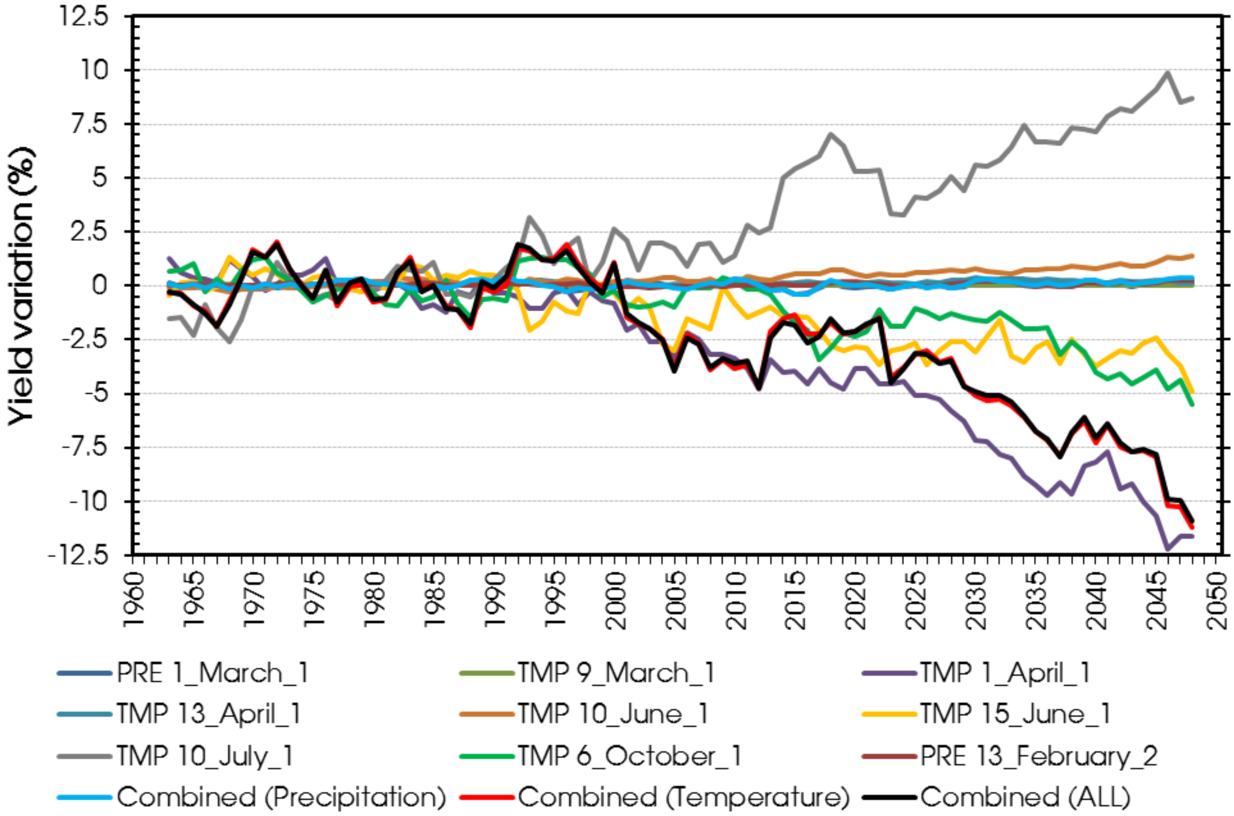


Figure 7.5: Separated and combined effects of precipitation and temperature changes on pineapple yield in Benin under SRES A1B+LCC changing conditions.

A close look at the Figure 7.5 reveals that the slight increase in precipitation in March of the first calendar year and in February of the second calendar year will have almost no effect on the pineapple yield. In fact, the two precipitation related predictors taken together will increase the pineapple yield up to just 0.42% by 2050. This minor impact of precipitation is even also indicated by the closeness of the curve of the overall potential pineapple yield changes (Combined (ALL)) and that of the contribution from the temperature-related predictors all taken together (Combined (Temperature)). The latter indicates that by 2050 up to -11.23% yield changes will be induced by the steady increase in mean near-surface air temperature. But one should note that similar to the precipitation-related predictors the variations of temperature related predictors in March and April (TMP 9_March_1 and TMP13_April_1) are also having nearly no impact on the yield variations in the future.

This Figure also reveals that some temperature-related predictors will have opposite effects on the pineapple yield in the future. Quite surprising, that is the case of TMP 10_June_1 and TMP 15_June_1 although they express the same physical quantity and this for the same month. In addition, in general future variations of the temperature related predictors TMP 10_June_1 and TMP 10_July_1 will have positive effects on the yield (up to +1.37% and +9.9% increase by 2050 respectively) whereas other temperature-related predictors namely TMP 1_April_1, TMP 15_June_1, and TMP 6_October will negatively impact the pineapple yield with respectively up to -12.21%, -4.89% and -5.52% yield reduction induced by 2050. The highest positive impact (+9.9% by 2050 at the rate of +1.61% in 10 years) arises from temperature increase in July while the highest negative impacts comes from temperature increase in April (-12.21% by 2050 at the rate of -2% in 10 years). On overall, the pineapple yield under the combined effects of all predictors shows a decreasing trend in the future, implying that the positive contributions from TMP 10_June_1 and TMP 10_July_1 were not strong enough to counterbalance the negative temperature effects in other important months.

8 MODELLING FUTURE AGRICULTURAL YIELD IN BENIN FOR THE STAPLE FOOD AND CASH CROPS

This Chapter presents the results for the other crops investigated in this study. Statistical crop models were developed for various staple crops grown in the republic of Benin. These crops belong to the groups of cereals, legumes, fibre, roots and tuber food crops and are quite important for ensuring food security and export earnings in Benin. For each of these crops future climate signals as projected by REMO RCM were translated into potential yields / yield changes. Therefore the projected yield changes under future climate change conditions are presented after showing the performance of the crop models they arose from. Further analyses for attribution of the changes led to separation of the effects of precipitation and mean near-surface air temperature. As well the indirect effects of land degradation in sub-Saharan Africa on the potential crop yield changes are also demonstrated.

8.1 Performance of the crop models and selection of the most important climatic predictors

In this study the impacts of climate variability and future climate change on some other crops grown in Benin are also investigated. Among these is cotton; a fibre crop cultivated in the republic of Benin exclusively for export. The other crops are staple food crops belonging to the groups of cereals (maize, rice, sorghum), legumes (cowpeas, groundnuts), and roots and tuber (cassava, yams). All these crops are quite important to ensure food security and export earnings in the republic of Benin. In the context of the diversification of the Beninese agriculture it is urgent to study the climate – agriculture nexus and predict the attainable yield under the uncertain future climate so as to efficiently tailor the need for crops promotion and adaptation strategies to develop in case a crop is to be severely affected by the looming climate change effects. In this regard, statistical crop models were developed for each of these crops. The crop models were trained and validated with historical yield data aggregated at a national level and extending over the crop production years 1970/1971 to 2009/2010. Figure 8.1 shows the distribution of R square and Brier-Skill-Score (BSS) among the 1000 individual models per crop as well as the performances of the ABMA – combined crop models. The ABMA method for multi-model combination was found more robust in Chapter 6 (see section 6.3) and thus applied to average the individual crop models presented in this Chapter.

While looking at the BSS only it can be seen that, apart from cassava, the 1000 individual models of all the crops have good forecast skill above mere reproduction of the long-term historical average yield. The combined models perform better than most of the individual models as their BSS and R square are close to those of the individual crop model with the highest performance.

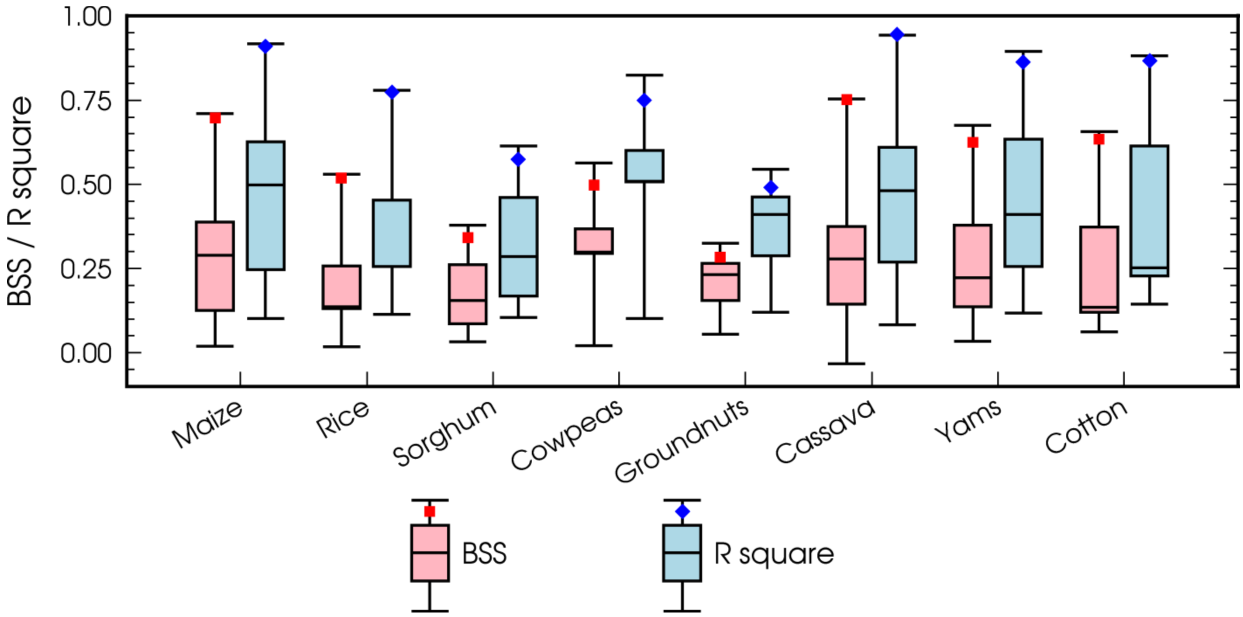


Figure 8.1: Performances of the statistical crop models developed for Benin agriculture.

The lower and the upper of the box indicate respectively the first and the third quartiles of the distribution of a specific performance indicator (BSS or R square) derived from 1000 individual models per crop. The bar in a box indicates the median of the distribution. The whiskers extend to the extreme of the distributions. The dots stand for the performance of the combined models following the ABMA multi-model combination technique.

Comparison of the crops on the basis of the R square of the combined models reveals that the crops are diversely sensitive to climate variations. The climatic factors considered in this study are precipitation and mean near-surface air temperature. In the group of cereals on average around 91% of the variability in maize yields could be explained by climate variability. Climate also explains 77.4% and 57.4% respectively of the variability in rice and sorghum yields. For the legume crops the results suggest that respectively 74.9% and 49% of the variability in cowpeas and groundnuts yields are induced by climate. In the group of roots and tuber crops 94.4% of the cassava yield variability and 86.2% of that of yams could be attributed to the variability of climate. Finally for cotton, climate explains 86.6% of the yield variability. Thus agricultural production in Benin is highly driven by climate fluctuations. The unexplained part of the total variability in the yields could be attributed to non-climatic factors like the crop cultivars selected, the infestation of the crops, the farm management practices, the soil nutrient status and the soil types.

Table 8.1: Most important predictors per crop and their effects on the crop yields.

Rank	Maize	Rice	Sorghum	Groundnuts	Cowpeas	Cassava	Yams	Cotton
1	PRE3_Apr (−)	TMP19_Jun (+)*	PRE15_May (+)	TMP19_Apr (+)*	TMP2_Jun (+)*	PRE14_Mar_1 (+)	PRE9_Jun (−)	TMP10_Oct (+)*
2	TMP7_Apr (+)	PRE8_Sep (+)	PRE19_Jun (+)*	TMP3_May (+)	TMP14_May (−)*	TMP7_Feb_2 (+)*	PRE15_Mar (+)*	PRE6_Jul (−)*
3	TMP9_May (+)				TMP14_Mar (−)	TMP14_Apr_2 (−)	PRE18_Aug (+)*	TMP13_May (+)
4	TMP3_Jul (+)				PRE5_Jun (+)	TMP17_May_1 (+)	TMP19_Mar (−)	TMP2_Jul (−)
5	PRE14_Sep (−)*				TMP10_Mar (−)	PRE16_Oct_1 (+)	PRE3_Feb (−)	TMP18_May (−)
6	PRE6_Oct (+)					PRE9_May_1 (−)		TMP20_Sep (+)*
7	PRE19_Oct (−)					TMP12_Oct_1 (−)		

(+)/(−): Sign of the regression parameter associated with the predictor *: Correlation of the predictor with the yield is statistically significant at 1%

Monthly large/small scale climate information regarding those two climate variables were used to drive the crop models. Table 8.1 presents the most important climate predictors for each of the crops investigated. In Table 8.1 for a given crop a predictor is considered as very important only if the sum of the posterior probabilities of the single models in which it is included is higher than or equals 90%. For each crop the more important predictors were ranked in a decreasing order of importance based on the aforementioned criteria. The effect of a given predictor on the yields of a specific crop is to be interpreted in light of the sign of the partial regression parameters associated with the predictor, the sign of the spatial loadings of that predictor over Benin (shown in Appendices A & B), and the temporal evolution of the predictor (shown in Appendices E to L). Following the criteria for the selection of the most important predictors, Table 8.1 reveals that in the group of cereals precipitation in April, September and October is a limiting factor for the production of maize. Meanwhile temperature in April, May and July is also quite important for the production of maize. But the most important determinant of maize production in Benin is precipitation in April. On the contrary, for the production of rice the most important predictor is related to temperature in June. An increase in mean near-surface air temperature in that month will boost the production. But precipitation in September is also quite important for the production of rice. In this same group of cereals the production of sorghum is found to be more influenced by only the variations of precipitation particularly in May and June. Precipitation in May is likely to have the greatest effect on the yield of sorghum during the growing season.

In the group of the legume crops the production of groundnuts is found to be more sensitive to temperature variability in April and May while the production of cowpeas will react more to the variations of temperature in March, May and June. Contrary to groundnuts, the production of cowpeas is also highly sensitive to precipitation in June. The greatest effects of temperature are expected in April and June respectively for groundnuts and cowpeas.

For cotton the results show that precipitation in July is quite important. Any increase above the long-term mean (mean over the reference period P1: crop production years 1970/71 to 2008/09) will induce a decline in cotton yield. Besides precipitation in July, the results suggest also that temperature in May, July, September and October are very important. Quite surprisingly the greatest climate induced effect on cotton yield is coming not from a precipitation related predictor but from temperature variability in October. As evidenced by the positive sign of the regression coefficient associated with that predictor, an increase in temperature in October will have a positive impact on cotton yield.

For both yam and cassava the most important predictors are related to precipitation. These are precipitation in March for cassava and in June for yams. In general for yams, precipitation in February, March, June and August is very important. In all those months any precipitation increase will positively impact the yield whereas temperature increase in March will have the opposite effect on the yield. Meanwhile for cassava – a root crop – precipitation is in general very important during the first calendar year of the growing season especially in March, May and October. Not least important are also temperature in May and October of the first calendar year and in February and April of the second calendar year of the growing season.

8.2 Separated and combined effects of precipitation and temperature on agricultural yield changes

The crops investigated in this study respond in different ways to increasing temperature and changing precipitation patterns. Table 8.2 shows the average yield changes and the rates of the occurring changes during the first-half of the 21st century. Meanwhile Figure 8.2 displays more details on the temporal evolution of the projected changes under different anthropogenic forcing conditions. It can be seen from both Table 8.2 and Figure 8.2 that during the 21st century the production of cotton, yams, rice, and to a lesser extent sorghum, will benefit from climate change as projected by REMO RCM. Meanwhile climate change will limit the production of groundnuts, cowpeas, cassava and maize. Hence the impacts of future climate change in agriculture in Benin could be compared to a game making winners and losers. To ease the comparison among crops, for each agricultural commodity the yield changes were computed relative to the average yield of the specific crop over the production years 1995/1996 to 2008/2009. The extent to which these changes will happen varies among crops. For all these crops the predicted yields fluctuate from year-to-year, but still a clear deterministic tendency toward either reduction or increase can be derived. In the analysis below emphasis is put on the model outputs under the combined scenarios A1B (GHG+LCC).

Table 8.2: Mean and trend of the projected agricultural yield changes in Benin under changing future climate conditions (2001-2050).

	Reference yields (Kg/Ha)	Future yield changes (%) under different anthropogenic forcing scenarios					
		B1 (GHG+LCC)		A1B (GHG)		A1B (GHG+LCC)	
		Average	Trend	Average	Trend	Average	Trend
Maize	949.95	-3.346	+0.104	-5.654	-0.900	-5.889	-1.354
Rice	2004.24	+6.884	+7.520	+11.624	+9.531	+10.200	+8.325
Sorghum	834.04	-4.070	-1.512	-1.585	+3.280	-2.941	+1.684
Groundnuts	771.36	-5.456	-1.198	-7.752	-0.882	-6.768	-0.284
Cowpeas	569.03	-12.739	-5.203	-11.140	-4.245	-14.166	-5.254
Cassava	8797.34	-10.289	-3.350	-5.679	-2.447	-12.388	-4.457
Yams	10641.45	+1.920	+0.735	+0.100	-0.119	+3.370	+1.088
Cotton	1000.01	+6.332	+1.778	+2.602	+1.034	+5.922	+3.144

The reference yields refer to the average of the detrended yields over the crop production years 1995/1996 to 2008/2009 retained for inter-crops comparison. For each crop, the yield changes are computed relative to the reference yield. The average yield changes and the trends are computed for the time period 2001-2050 with the projected yield changes shown in Figure 8.2. The trends are expressed as percentage of yield changes per decade.

The highest yield increases are expected for rice and cotton. The rice yields will increase by up to 10% from 2001 to the 2020s. After 2030 the increasing tendency shows an enhancement so that on average it is projected up to approximately 39% increase of rice production per unit of cultivated cropland in the 2040s. On overall the results reveal that during the first-half of the 21st century rice yields are projected to increase at a rate of 8.3% per decade. Meanwhile cotton yield will also increase by 3% per decade, up to 24.3% in the 2040s.

Uncertainty in the multi-model estimates in the future, especially after 2020, is bigger for rice and cotton compared to the other crops. This is particularly true for rice for which the 95% confidence interval for the yield change by 2050 displays a quite huge spectrum, thus reflecting large disagreement among the estimates from the 1000 single rice models. According to that confidence interval the changes in rice yields by 2050 will range between 34% reduction and 107% increase although the multi-model average rice yield change by 2050 is projected to be about 39% increase. As suggested by the crop models climate change will also be in favour of the production of sorghum and yams whose yields will increase up to approximately 10% during the first-half of the 21st century respectively at the rates of 1.7% and 1.1% per decade.

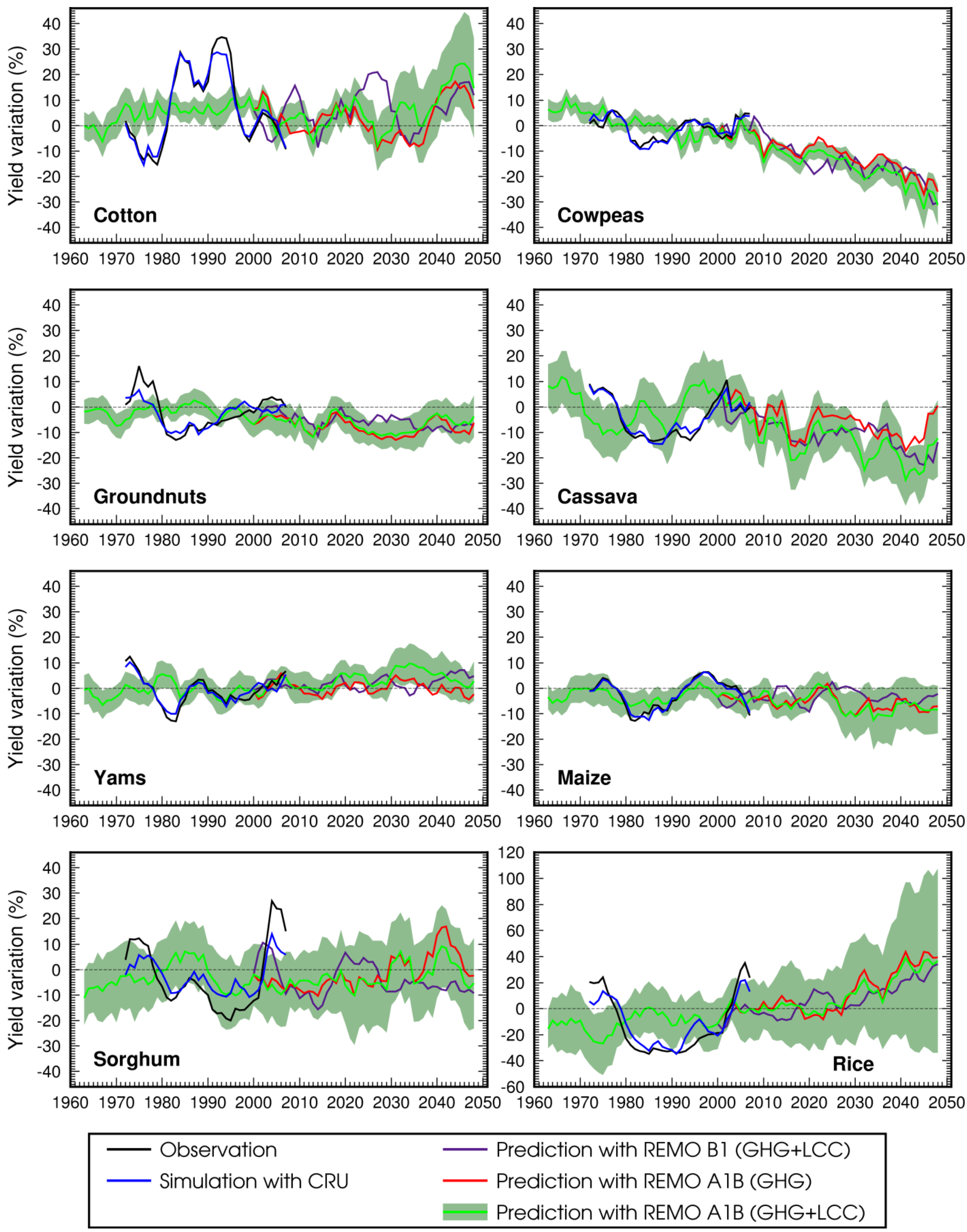


Figure 8.2: Projection of agricultural yield changes in Benin under different climate change scenarios according to REMO RCM simulations.

The yield changes are computed relative to the average yield over the crop production years 1995/96 to 2008/2009. 5-years running mean is further applied. The confidence intervals are shown for only the yield projections under REMO A1B (GHG+LCC).

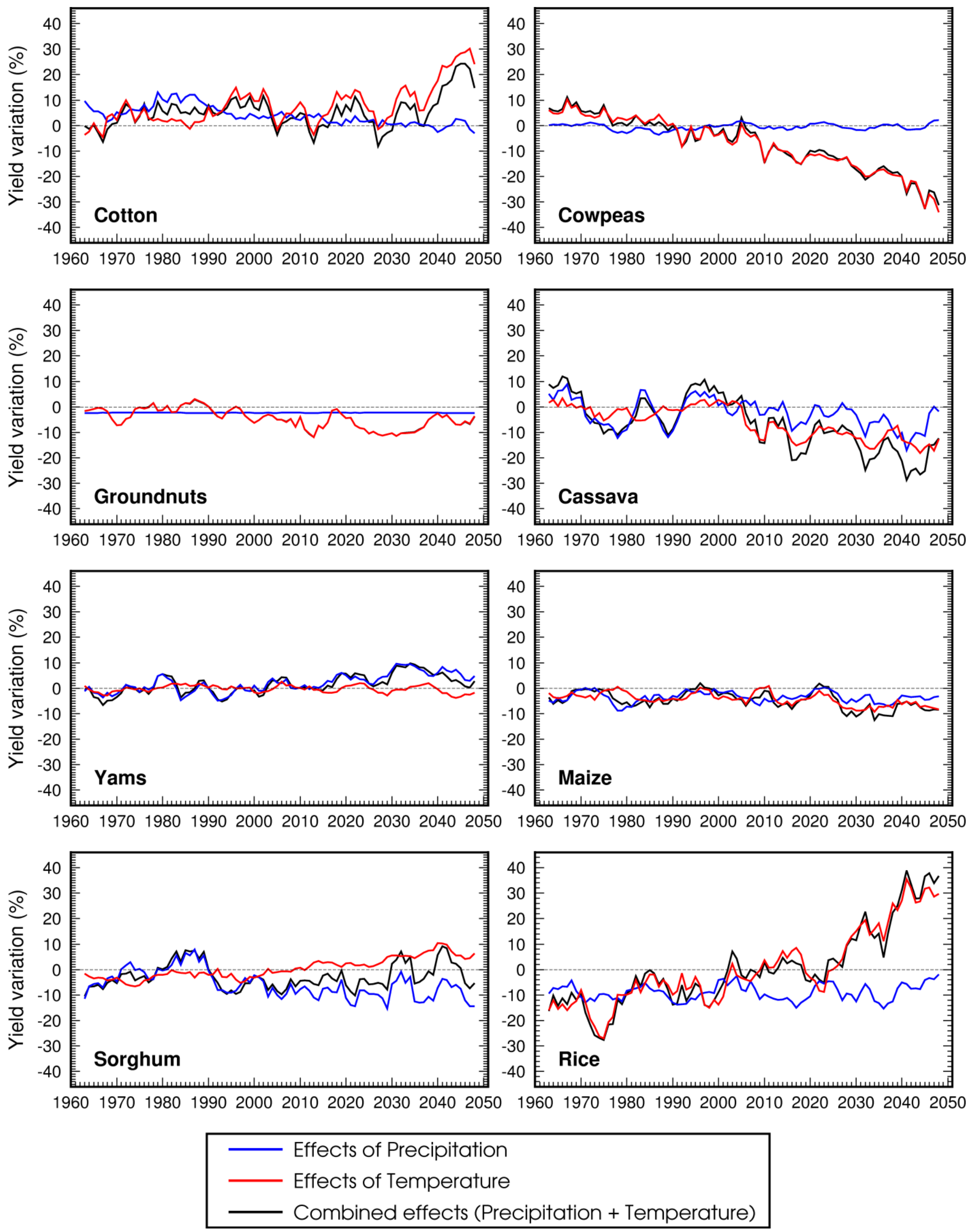


Figure 8.3: Projection of separated and combined effects of precipitation and temperature on the yields of some agricultural commodities grown in Benin.

For each crop, the yield changes are computed relative to the average yield over the crop production years 1995/1996 - 2008/2009. 5-years running mean is further applied. The effects on crop yields are shown under changing climate according to REMO A1B (GHG+LCC) simulations.

Unfortunately the production of cowpeas and cassava are going to be severely affected by climate change. For cowpeas it is seen that the yield reductions will reach up to approximately 33% by 2050. These reductions will be at the rate of roughly 5.3% per decade during 2001-2050. Meanwhile for cassava up to 29% reduction of the yields is to be expected by 2050. The future changes in the yield of cassava are projected to occur at the rate of about 4.5% yield reduction per decade. For maize and groundnuts respectively approximately -1.4% and -0.3% yield changes per decade are to be expected during the 21st century. Thus, the production of maize and groundnuts will display a downward trend, bringing the yield down up to about 12.5% reduction for both crops. Comparison of the yield reductions of those crops with that of pineapple shown in section 7.2 reveals that the projected yield reductions by 2050 are almost in the small range for pineapple, maize and groundnuts. It could not be stated that future climate change will have either positive or negative impacts on all crops. Some crops tend to gain from climate change while others stand to lose.

The crop yield changes as depicted above in the analysis of Figure 8.2 resulted from the coupled effects of precipitation and mean near-surface temperature. Separating these effects is crucial to identify for each crop which variable is limiting the production, and quantify to what extent the variations of these variables will be acting either positively or negatively in agriculture. Doing this will enlighten decision-makers and enable them to better target adaptation measures for drought or heat stress management in agriculture. In this regard Figure 8.3 displays the separated effects of precipitation and mean near-surface air temperature on the projected crop yields in times of climate change. The effects are shown under the driven REMO A1B+LCC transient climate simulations. With the exception of yams (+1.46% precipitation-induced increase per decade), during the time period 2001-2050 changing precipitation patterns as projected by REMO RCM will have negative effects on crop yields. These negative effects from precipitation vary from nearly no effects in the case of groundnuts to around 1.9% yield reduction per decade for cassava. Henceforth the yield losses due to changing precipitation patterns will amount up to -1.94%, -2,40%, -2.99%, -7%, -15.03%, -15.29%, and -17% respectively for cowpeas, groundnuts, cotton, maize, rice, sorghum, cassava. But, with respect to most crops, the effects of precipitation are minor when compared to those of mean air temperature. Temperature will have positive effects on some crops (e.g. rice, cotton, sorghum) and negative effects on others (e.g. yams, groundnuts, cowpeas, cassava, maize). On average the impacts of the heat stress will range between about 4% yield losses (e.g. yams) and 34% yield losses (e.g. cowpeas). For groundnuts all the negative impacts on the potential yields are induced by the heat stress. Nevertheless there is still some hope because the temperature increase will be beneficial to sorghum, cotton, and rice; those yields will increase respectively by about 10.5%, 30% and 35.5% by 2050 at the rates of 1.96%, 4.15% and 8.10% per decade.

The effects of both precipitation and mean near-surface air temperature on agriculture yield changes as shown above result from two drivers of anthropogenic climate change. Those drivers are greenhouse gas emissions and land cover/land use changes (Paeth et al 2009). Therefore both effects on agricultural yield changes can still be split each in two parts. In the following further investigations for attribution of agricultural yield changes point to the overall contribution from land use/land cover changes.

8.3 Contribution of future land cover/land use changes to agricultural yield changes

Land degradation is of major concern in tropical West Africa (FAO 2006; FAO 2010). From 2000 to 2010 the African continent lost 3.4 million hectares of forest per year (FAO 2010). The annual rates of deforestation between 1990 and 2010 were estimated to 0.46% for West and Central Africa, and between 0.49% and 0.56% for the whole of Africa (FAO 2010). According to Paeth et al (2009), FAO (2006) estimated that by 2050 the deforestation rate will increase up to 30% for the whole tropical Africa. Many studies had proved that land cover/land use changes influence global or regional climate (e.g. Pielke et al 2002; Ramankutty et al 2008; Mahmood et al 2010; Deng et al 2013; Wang et al 2013; Mahmood et al 2014; Yu et al 2014). Although in their simulations the vegetation-atmosphere interaction was not fully interactive so that the land cover might respond back the climate stimuli, Paeth et al (2009) reveal that land cover changes in sub-Saharan Africa can be held responsible for about 35% of the rise in mean near-surface air temperature, and one-third of the climatic drought tendency over tropical Africa.

The indirect effects of the land cover changes on agriculture yield changes in Benin could already be inferred from Table 8.2 and Figure 8.2 by comparing the crop outputs under the A1B (GHG+LCC) combined scenarios and the A1B (GHG). These two scenarios differ by the land cover changes that is set to be constant in the latter. But for a better understanding of the changes induced by land degradation, Figure 8.4 displays the relative contribution of future land cover changes to agricultural yield changes in Benin. The potential impacts of land degradation are assessed per crop here by computing the difference between the projected yield changes under the scenarios A1B (GHG+LCC) and A1B (GHG).

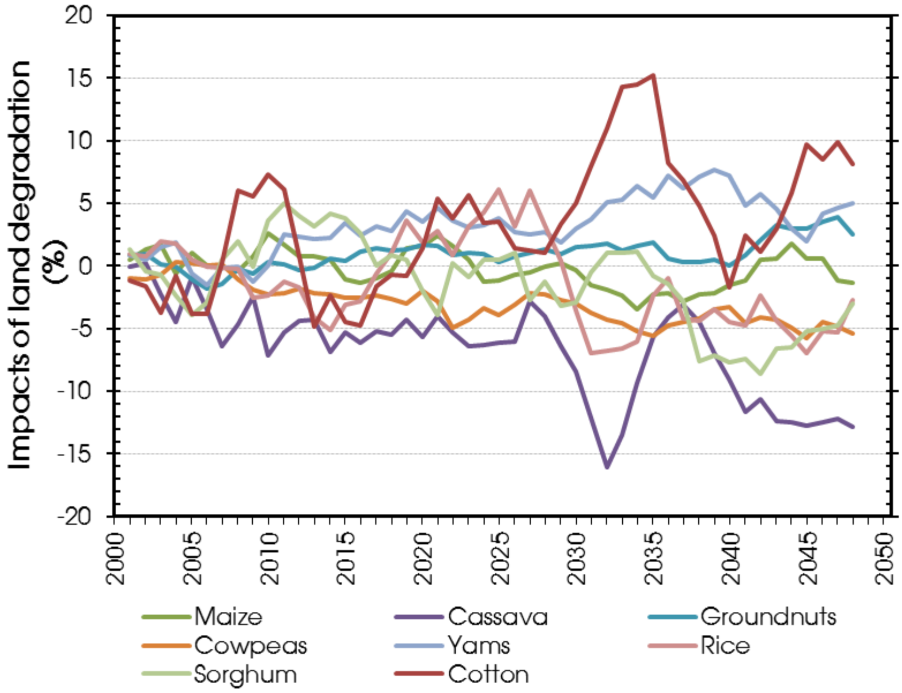


Figure 8.4: Relative contribution of land degradation to the projected agricultural yield changes in Benin.

As shown by Figure 8.4 during the first-half of the 21st century the on-going land degradation in sub-Saharan Africa will strongly boost the production of cotton and yams. For the other crops there are tendencies toward decreasing yields in the future. In fact, land degradation in sub-Saharan Africa can be held responsible of 0.5% to 2% yield losses per decade for maize, rice, sorghum, cowpeas and cassava. The decrease in potential yields due to land degradation will amount up to -3.43%, -5.74%, -6.98%, -8.58% and -16.04% respectively for maize, rice, cowpeas, sorghum and cassava. Here it can be seen that the three crops in the group of cereals are all negatively impacted by the land degradation processes. Meanwhile land degradation will also favour the production of groundnuts, yams, and cotton for which the yield increases it induces may amount up to 3.95%, 7.7% and 15.2% at the rates of 0.6%, 1.21% and 2.11% per decade. Relative to the combined effects of the two anthropogenic forces assumed herein the land use/land cover changes alone drive on average respectively 3.99%, 13.96%, 14.53%, 21.36%, 46.11%, 54.16%, 56.06%, and 97.03% of the changes in the production of maize, rice, groundnuts, cowpeas, sorghum, cassava, cotton and yams. From Table 8.2 it could already be seen that the effects of land degradation is so strong that even with weaker greenhouse forcing and lower amount of land cover/land use changes according to B1(GHG+LCC) the projected yield changes under B1(GHG+LCC) for cowpeas, sorghum, and to higher extent yams, cotton and cassava are above the ones under A1B (GHG) with stronger greenhouse gas forcing and constant land cover/land use changes.

9 DISCUSSION AND PERSPECTIVES

In this Chapter the key results are summarized and discussed in light of published literature. Some limitations of the study are highlighted as well as strategies to cope with or adapt to the negative impacts of climate change in agriculture. Recommendations are further derived and avenues are opened for better climate risk assessment and management in agriculture under changing future climate conditions in Benin.

9.1 Summary and Discussion of the key results

This study investigated the potential impacts of observed and future climate change on Beninese agriculture. The developed crop models performed quite well, confirming that climatic fluctuations largely govern agricultural yield changes in Benin as in most west African countries. The high dependence of West African agriculture on climate and weather patterns was already demonstrated in various published papers (Sivakumar et al 2005; Paeth et al 2008a; Roudier et al 2011).

With respect to most crops investigated in this study (e.g. pineapple, groundnuts, maize, cowpeas, and cassava) in the absence of any adaptation strategies agricultural yields in Benin will decrease by about 10% to 33% by 2050 due to changing precipitation patterns and increasing temperature. But the results presented are marked with some contrasts. Crops such as sorghum, yams, cotton and rice will benefit from future climate change. Further investigations for attribution of changes revealed that increasing mean-near surface air temperature influences more the future changes in the agricultural outputs than the reduction of precipitation amounts. With the exception of cotton, sorghum and rice, increasing mean air temperature will lead to more reduction of the yields. As well, it is found that through its large contribution to the reduction of precipitation amounts and the increase in temperature the degradation of forests and savannah ecosystems in sub-Saharan Africa will lead to more reduction of the future yields of the crops studied herein except groundnuts, cotton and yams.

Several studies have investigated the impacts of global and regional climate change on agriculture. By 2050s Jones and Thornton (2003) projected on average overall agricultural yield reductions in Africa in the range of -10% to -20%. With a high confidence the fourth IPCC assessment report (IPCC-AR4) on climate change impacts, adaptation and vulnerability concluded that, with up to 50% crop yield loss in some African countries already by 2020, it is likely that future climate change will severely weigh down on agricultural production and food security in Africa (Boko et al 2007). The conclusions of the fifth IPCC assessment report (IPCC-AR5) on climate change impacts are consistent with those of IPCC-AR4. In addition, it emphasises that, in comparison with the changes in precipitation patterns, temperature changes will have harsher impacts on crop yields across Africa (Niang et al 2014). In the same vein, reviewing several scientific evidence on climate change impacts on agriculture (n=1144) in regions including Africa, Knox et al (2012) reported projected agricultural yield changes amounting up to -40% across regions in Africa. They further indicated that on average the projected yield changes is about -8% by 2050s in Africa, and -12.5% particularly in West Africa. Meanwhile Müller et al (2011) reported in their review of 14 quantitative published literature on climate-induced African agricultural change that relative to the current level of agricultural production the published evidence using process-based crop model projected across Africa changes in the range of -84% to +62% while -57% to +30% were projected with statistical crop models. As well in their meta-analysis on the impact of climate change specifically on West African agriculture Roudier et al (2011) reported that in general a drop of future crop yields is predicted. They reported that predicted yield changes in West Africa lie in the interval of -50% and +90%. But the median value of the projected changes from the 16 studies included in their meta-analysis was -11% for the whole West Africa, and especially about -13% in the Guinean countries and -18% in the Sudano-Sahelian countries (Roudier et al 2011).

- Climate change impact on pineapple crop yields

There is paucity of information on climate change impacts on the production of pineapple. To the best of my knowledge, only Chang (2002) – using regression models for crop yields and synthetic climate data for future conditions – stated that temperature increases due to climate change tend to negatively affect the production of pineapple in Taiwan, with too much rain being also unfavourable for the yields. But this author did not indicate the magnitude of changes. Therefore, the projected pineapple yield changes in Benin under changing climate conditions cannot be compared with scholarly published evidence. This lack of publications on climate change impact on pineapple production is certainly due to the very limited number of relevant physiologically-based, process-based pineapple crop simulation model. Indeed before the recent development of the pineapple crop model SIMPIÑA (Dorey et al 2015) there were no model capable of simulating pineapple growth, development and yield. As reported the SIMPIÑA pineapple model was designed to simulate the development and growth of the pineapple cultivar Queen Victoria. To date the model is calibrated and validated only on the Réunion Island conditions where it showed very good performance (Dorey et al 2015). But performance of this model in environmental conditions such as those occurring in tropical West Africa is still not evidenced. As well it is not yet reported whether this model can be adapted to the Smooth Cayenne and Sugarloaf cultivars largely grown in Benin and West Africa. The ALOHA-pineapple model (Zhang and Bartholomew 1992) previously designed to predict the growth, development and yield of the Smooth Cayenne cultivar in Hawaii and reported to perform well under a wide range of environmental conditions including those in southern Côte d'Ivoire is no longer operational (Zhang et al 1995). Other pineapple models are designed to simulate specific processes in pineapple (e.g. heat-unit model, harvest date model) or intercropping (e.g. SURHIS model) (Jalloh et al 2009). That is the case with a heat-unit model designed to simulate the fruit growth of Smooth Cayenne (Fleisch and Bartholomew 1987) as well as a model designed for the prediction of the harvest date of the pineapple Smooth Cayenne (Malézieux et al 1994).

It is well-known that climate variations largely influence the production of pineapple. In China Man-yuan et al (2009) showed that pineapple production in the Hainan Province is closely related to climate. Near the Republic of Benin Iwuchukwu and Udoye (2014) indicated that most pineapple growers in Nigeria reported that their production is harmed by excessive heat and irregular rain, with declining yield, farm size and income being the perceptible climate change effects on their production. According to Man-yuan et al (2009) and Malezieux et al (2003), temperature, precipitation, humidity, sunshine hours and wind are the main factors driving the growth, development and yield of pineapple. Among those factors temperature is most probably the one with the highest importance (Py et al 1987; Malézieux et al 2003; Paull and Duarte 2010). Although pineapple is able to grow in areas where temperature ranges from 15°C to 30°C, the optimal growth temperature for pineapple is about 24°C. The plant growth is delayed with air temperature variations falling outside the range of 15-30°C (Malézieux et al 2003). Thus, pineapple is not able to tolerate extreme air temperature. Regarding precipitation, the findings of this study suggest that precipitation is not a limiting factor for pineapple production in Benin. Correlation analysis in this study revealed that during the growing cycle pineapple is sensitive to changes in precipitation only in march of the first calendar year and February of the 2nd calendar year. Those months belong to the dry season in West Africa. In general in the west African dry season corresponding to the European wintertime rainfall events are rare (Knippertz and Martin 2005; Knippertz et al 2008; Knippertz and Fink 2009). According to Malezieux et al (2003) pineapple can be grown in areas with low rainfall amounts. A minimum of just 50 mm/month throughout the growing cycle is required to sustain pineapple growth (Hepton 2003). The well-adaptation of pineapple to low rainfall conditions and its high water-use efficiency are said to be due to its crassulacean acid metabolism (CAM) photosynthetic pathway (Malézieux et al 2003). It is reported that during the day the stomata of the pineapple leaves are closed, thus reducing transpiration. Then transpiration of the pineapple plants occur during the night when air temperature is generally cooler than during the day (Malézieux et al 2003). But Malezieux et al (2003) still made it clear that the production can be negatively affected by drought conditions. Despite its great capacity to survive drought periods (Sideris and Krauss 1928), Malezieux (1988) showed that important rainfall deficit during the vegetative phase of pineapple can significantly delay the growth. He further indicated that water deficit after flowering can also affect the weight of the fused fruitlets and thus the yield. In general the rate of CO_2 assimilation by the pineapple plant is proven to decline with drought; particularly prolonged drought, and increasing temperature can accelerate this rate (Malézieux et al 2003; Lin et al 2006). But the effects of water stress on the pineapple plant are also proven to be reversible when the plant is again well-watered thereafter (Cote et al 1993; Malézieux et al 2003).

The developed pineapple crop model showed that the yield changes are positively correlated with precipitation in respectively March of the first calendar year and February of the second calendar year. Under future climate change conditions the slight increase in precipitation in those two months cannot be able to compensate for the overall negative effects of the increase in mean air temperature. Therefore irrigation of the pineapple fields, and this particularly during the dry season, can improve the production. Malezieux et al (2003) reported that, near the republic of Benin, irrigation together with polyethylene mulch are already used in pineapple exploitations in Cote d'Ivoire. The latter technique can help for soil water conservation (Combres 1983; Malézieux et al 2003) by maintaining a relatively good level of soil humidity and reducing evaporation while also protecting the plant against burning.

The pineapple crop model developed herein is solely based on monthly mean air temperature and does not take into account any difference between diurnal and nocturnal air temperature changes. Mean air temperature of 25°C with 10°C diurnal range is the optimal temperature condition for the growth of pineapple (Neild and Boshell 1976; Malézieux et al 2003). But pineapple growth decrease very fast at mean temperature below 15°C and above 32°C (Neild and Boshell 1976; Malézieux et al 2003). In the absence of any other stress factor the growth rate of pineapple plant is strongly influenced by temperature especially night temperatures (Friend 1981; Bartholomew 1982; Malézieux et al 2003). The increase in night temperature about 26°C decrease the net CO_2 uptake (Neales et al 1980; Zhu et al 1999; Malézieux et al 2003) and the dry-matter accumulation of the plant (Malézieux et al 2003). As reported by Malezieux et al (2003), Bartholomew (1982) found that cool night temperatures (18–22°C) and warm diurnal temperatures (26–34°C) are more favourable for dry-matter accumulation by the pineapple plant and the growth rate of the plant than diurnal and nocturnal temperatures both warm (around 30°C). As well, higher water use efficiency is reported when night temperature is low (Malézieux et al 2003). Chemical induction of flowering in pineapple is desirable to allow synchronisation of the harvest (Malézieux et al 2003; Paull and Duarte 2010). In Benin most of the pineapple growers forces this floral initiation between 9 to 13 months after planting by means of calcium carbide (CaC_2) (Fassinou Hotegni et al 2010). But it is also reported that air temperature above 28°C makes chemical flower induction more difficult and leads to linear decrease in the percentage of plants forced (Paull and Duarte 2010). The growth of the fruit is also under the control of temperature which while associated with solar radiation can negatively influence the fruit quality (Paull and Duarte 2010). As the highest effect of mean air temperature on pineapple yields is coming from the increase of mean air temperature in April, farmers should be encouraged to start planting after the month of April while not adopting any adaptation strategy. As well, because the crop model showed that temperature increase is the major cause of the projected decrease in pineapple yields, adaptation of the pineapple production systems in Benin should be regarding heat stress management. Besides development/selection of heat-tolerant crop variety, protection of the pineapple crop from the heat effects could be a valuable solution. Liu and Liu (2012) already demonstrated the effects of shading around pineapple plants in reducing temperature stress and increasing relative humidity.

- Climate change impact on cereal crop yields

Yams, cassava, and maize are the major staple food crops cultivated in the Republic of Benin whereas rice is the fourth most important in terms of consumption volume while cotton is the major cash crop (Igue et al 2000; Lawin et al 2013). But most of the scientific publications on climate change impacts on African agriculture are related to maize (Müller et al 2011; Roudier et al 2011; Knox et al 2012; Jalloh et al 2013b; Cairns et al 2013). Maize is said to be a niched crop in West Africa (Jarvis et al 2012; Challinor et al 2015). It is the most important staple food crop in southern and central Benin, but it is more cultivated in the southern regions than the central zones of the country (Igue et al 2000; Lawin et al 2013). Provided good rainfall conditions, it yields more than many small grains (Alumira and Rusike 2005; Rurinda et al

2014). This study reveals that maize yield in Benin will decrease up to about 12.5% by 2030s under REMO (SRES-A1B + LCC) scenario. Many authors have already pointed to reduction of maize production across Africa due to climate change. Lobell et al (2008) projected that by 2030 maize yield will decrease by 30% in southern Africa while sorghum will decrease by just 2%. Schlenker and Lobell (2010) projected maize yield changes amounting on average to 22% reduction by 2050 in sub-Saharan Africa. Jones and Thornton (2003) indicated about 10% decrease in maize yields by 2055 in many African countries including the Republic of Benin. Tesfaye et al (2015) indicated that West Africa will experience 11% to 21% decline in maize yields by 2050. Using the global vegetation and agricultural model LPJmL (Sitch et al 2003; Gerten et al 2004; Bondeau et al 2007), Waha et al (2013) predicted that in West Africa (below 13°N) slight negative changes of about -10% to +6% are to occur in maize yields during the time period 2056-2065. Tingem and Rivington (2009) predicted declining future maize yield in the range of +27.1% and -69.1% in Cameroun. Knox et al (2012) reported -5.4% shortfall in average maize yield changes in Africa by 2050s with on average -7.4% changes in West Africa. According to Knox et al (2012) the projected changes in maize yields across West Africa vary between -20% and +26% with roughly -17% changes in Benin. Ahmed et al (2015) projected for Benin maize yield decline in the range of 16.9% to 50.4% by 2050 (2041-2050). According to Jalloh et al (2013) by 2050 maize yield loss of 5% to 25% is predicted in most productive zones of maize in the countries along the Guinea coast based on the outcomes of the global climate models CSIRO Mark 3 and MIROC 3.2 under the SRES A1B scenario forcing the DSSAT crop model. Ahossane et al (2013) projected similar yield changes for Cote d'Ivoire using the same climate – crop model combinations. Particularly in the Republic of Benin reduction of maize yield in the range of 5-25% is projected with the same global climate models forcing a DSSAT crop model in the southern and central parts where maize in mainly grown (Lawin et al 2013). But for the central and southern parts of Benin, projection with the CSIRO Mark 3 GCM suggest maize yield loss higher than 25% (Lawin et al 2013). Meanwhile using an empirical crop model forced with REMO RCM nested in the coupled GCM ECHAM5/MPIOM (Paeth et al 2009), Paeth et al (2008a) projected up to about 12% maize yield reductions for Benin by 2020s. Investigating also the impacts of climate change on maize production in Benin using the EPIC crop model forced with climate projections from Paeth et al (2009), Regh et al (2014) indicated for 2050 yield changes in the range of -30% to -50% under the socio-economic B1 scenarios and -50% yield changes under SRES A1B especially in the northern Benin, whilst predictions from Gaiser et al (2011) for the upper Ouémé catchment area in Benin and using also the same climate-crop model combination suggested up to 56% maize yield reductions for the time period 2041-2050. In view of the scale of projected maize yield loss under future climate conditions the fundamental question arising is whether the production could still be sufficient and stable to meet the needs of the increasing population and ensure food security (Rurinda et al 2014).

For sorghum, using the CropSyst impact model forced by GISS and HadCM3 GCMs, Tingem and Rivington (2009) showed that across Cameroun the projected changes are highly variable in space with substantial yield reductions in some regions and little or no change in others. In their highly robust meta-analysis, Knox et al (2012) reported -15% losses in sorghum yields in Africa by 2050s with no significant variations across the continent, whilst Schlenker and Lobell (2010) projected an average of 17% decrease in sorghum yields by 2050 in sub-Saharan Africa. A more recent study focusing on the West African countries revealed that sorghum yield will decrease by 5-25% across West Africa, with Benin experiencing more than 25% decline particularly in the southern and central parts of the country under CSIRO A1B future climate (Jalloh et al 2013a). Ahmed et al (2015) reported sorghum yield changes in Benin between -15.3% and +30.3% by 2050 (2041-2050) with different future climate scenarios. Salack (2006a) indicated that by 2050 sorghum yields will vary by about 0% to 14% decrease in Burkina-Faso and by -8% to -11% in Niger while assuming no changes in precipitation and 1.5°C increase in temperature. He further showed that with decreasing precipitation as experienced during the time period 1941–2000 more reduction in sorghum yields in the range of -50% to -70% are to be expected. In the same vein Sultan et al (2013) showed that negative climate change impacts up to -41% yield changes are to be expected for sorghum in West Africa. Contrary to these evidence the outcomes of the present study reveal for sorghum that although the long-term average yield changes is negative (i.e. 2001-2050) it shows a positive trend in the future yield changes in Benin. In fact this study shows that 10% increase in sorghum yields may be experienced by 2050. Sonneveld et al (2011) confirmed these positive changes in the production of sorghum in Benin under climate change. Ahmed et al (2015) also suggested that by 2050 sorghum yield may significantly increase in most countries in West Africa. The projected reduction in precipitation amounts according to REMO RCM future simulations (Paeth et al 2009) may still suggest favourable conditions in Benin for the production of the drought-tolerant and –adapted sorghum (Jalloh et al 2013a). In general among the cereal food crops it is demonstrated that sorghum is more resistant to heat and water stresses than maize (Frere 1984; Makadho 1996; Fischer et al 2005; Knox et al 2012; Rurinda et al 2014). In fact sorghum is well known for its good performance in dry environments like the

Sahelian countries (Frere 1984; Rurinda et al 2014). As a result of this suitability to dry conditions scholars such as Makadho (1996) and Lobell et al (2008) suggested that farmers should replace maize production by traditional small grains such as sorghum and millets to sustain food provision. Those small grains are even rich in minerals and vitamins (Hulse et al 1980; Rurinda et al 2014). But Rurinda et al (2014) pointed to the controversy of that solution due to the lack of agreement among crop models (Knox et al 2012), and among their driven climate models outputs especially relating to the sign and magnitude of precipitation changes (Sivakumar et al 2005; Paeth et al 2011b) in most parts of sub-Saharan Africa. Furthermore it was stressed that such alternative solution is back neither by field-based experiments nor by farmers' knowledge (Rurinda et al 2014).

For rice, the results of this study are in good agreement with most of the reported rice yield changes in times of climate change, at least on the direction of the changes. This study suggest that rice yields in Benin will increase up to about 10% from 2001 to 2020s and reach 39% increase by 2040s. The vast majority of studies on rice yield and production responses to climate change focuses on the countries in Asia particularly those in south Asia, Korea, China (Lobell 2007; Kim and Pang 2009; Maharjan and Joshi 2013; Daccache et al 2014). Very few studies have been reported in sub-Saharan Africa, although in this part of the world the production of rice and its consumption have both substantially increased in recent years at the average annual rates of respectively 3.23% and 4.52% (Knox et al 2012; Sié et al 2012; Daccache et al 2014). For South Africa and East Africa Lobell et al (2008) reported an increase in rice yields between 4% and 5% by 2030s. In Malawi, Daccache et al (2014) projected by 2050s on average +8% and +5% increase in yields for rainfed and irrigated rice respectively. Some increases in the production of rice in Nigeria under climate change conditions were also reported by Adejuwon (2006). Especially in northern-Benin and the Sahelian part of West Africa Jalloh et al (2013) showed that 5% to 25% yield gain of rainfed rice is to be expected by 2050 whereas significant reductions are predicted in southern-Benin. But Paeth et al (2008a) suggested up to 9% decline in rice yields by 2025. Meanwhile in the Sahel region, with a DSSAT crop model suite, Salack (2006b) projected that under SRES B2a scenario the yield of rainfed rice will not significantly change by 2020, but by 2050 it will increase by 3–8% in Burkina-Faso, Mali and Senegal. For irrigated rice it is projected up to 4% yield loss by 2020 followed by a regain up to 10–18% in 2050 in Niger (Salack 2006b). As a result of 2°C increase in temperature, 1.5x CO_2 increase relative to the current baseline of 330 ppmv, and 5% to 10% decrease of May to September precipitation by 2050 it was also predicted a shortening of the development phase and the growing cycle of both rainfed and irrigated rice in the Sahel region (Salack 2006b). The increase in rice yields reported by Salack (2006b) was found more important when water was not a limiting factor for the production. In the Republic of Benin, with the exception of the north-western part of the country where rainfed rice is still cultivated, most of the production of rice occurs in inland valleys where water is still more or less permanently available. In few places across the country surface water or shallow groundwater irrigation practices are applied in the rice production systems (Totin et al 2012; Djagba et al 2014). Investigating the issues of rice yield responses to higher temperatures with minimum, mean daily and maximum temperatures respectively in the ranges of 22.1–23.7°C, 25.9–27.2°C and 29.2–31.4°C based on correlation analysis Peng et al (2004) claimed that rice yields drop by 10% for each degree Celsius (°C) increase in night temperature and about 15% per °C increase in mean daily temperature from global warming during the crop growing season whereas the influence of maximum temperature on the rice yield was found non-significant. Similarly in the same environmental conditions and using the same data Sheehy et al (2006) applied both a mechanistic and an empirical crop model and suggested that the rice yield change amounts to about -6%.$°C^{-1}$ at the baseline yield at average mean daily temperature of 26°C when the temperature increase is still below the level that cause infertility in rice. These findings are still opposed to the tied positive linear relationship between rice yields and the increases in mean air temperature obtained in this study. Daccache et al (2014) reported large uncertainty in their average rice yield projections while considering three different GCMs outputs and the SRES B1 and A2 scenarios. But the range of uncertainty they obtained is lower compared with the robust uncertainty in rice yield projections estimated in this study. In India it was reported that projected climate change impacts on rice yields could be largely biased by up to 32% due to uncertainty inherent to climate change scenario, crop model, and crop management (Daccache et al 2014). However, in view of the very limited number of studies on climate change impacts on rice crop yields in Africa, Knox et al (2012) argues in their meta-analysis that clear conclusion cannot be drawn as to what extent and in which direction rice yields will be impacted across Africa. This led them to conclude no mean change in future rice yield in Africa.

- Climate change impact on legume crop yields

For the legume crops - groundnuts and cowpeas - the outcomes of this study are also in line with the reported yield changes across West Africa. This study suggests that in Benin cowpeas may experience yield decrease up to about 33% by 2050 whereas the projected decline for groundnut yields will amount up to 12%. Schlenker and Lobell (2010) projected changes in groundnuts yields amounting on average to 18% yield reductions by 2050 in sub-Saharan Africa. Under rainfed conditions, 5–25% yield loss for groundnuts was projected across West Africa by 2050 (Jalloh et al 2013a; Somé et al 2013), while yield projections with the CSIRO A1B and MIROC A1B future climate pointed to more than 25% decrease in southern Benin (Jalloh et al 2013a). Paeth et al (2008a) projected yield reductions down to about 17% reductions by 2020 for both groundnuts and cowpeas in Benin. Meanwhile Duivenbooden et al (2002) indicated by 2025 production loss estimated between 11% and 25% for groundnuts whereas that of cowpeas amounts up to 30%.

- Climate change impact on the yields of roots and tuber food crops

In the group of roots and tuber food crops the results of this study suggested substantial yield losses for cassava and slight yield gain for yams. In fact this study shows that on average yam yields may increase up to 10% during the time period 2001-2050 whereas cassava may experience yield decline amounting up to 29%. The yield gain obtained for yams is likely mainly due to an increase in future precipitation in August as shown by the temporal evolution of the climatic predictors for that month used in the yam crop model. Compared to the literature these findings for cassava and yams are marked with some contrasts. Knox et al (2012) showed future yield changes for cassava varying between 0% and -53% in Ghana. They also reported a slight decline in the productivity of yams in West Africa. Using a robust statistical crop model, Schlenker and Lobell (2010) projected an average of 8% yield reduction for cassava in sub-Saharan Africa by 2050s. But contrary to the previously reported yield changes, Paeth et al (2008a) indicated that during the first-quarter of the 21st century both the production of cassava and yams in Benin will not be affected by climate change. Meanwhile Jarvis et al (2012) found that cassava is suitably adapted to the projected future climates in many regions across Africa, with -3.7% to +17.5% changes in climate suitability, and concluded that the cultivation of cassava in Africa could be a valuable alternative considering future climate change. Using the same regional climate model outputs as Paeth et al (2008a), but with a different crop modelling approach, Srivastava et al (2012) indicated that a decline of the productivity of yams up to -33% is to be expected until 2050.

- Climate change impact on fibre crop yields

Cotton is understudied in the literature devoted to climate change impacts on agriculture. This study reveals that cotton yield in Benin may increase up to 25% by 2050. Schlenker and

Roberts (2009) indicated that the yields of cotton may increase with temperature up to 32°C and decrease thereafter. Gérardeaux et al (2013) reported that during the first-half of the 21st century the production of cotton in Cameroon will increase with an average rate of 1.3 kg.Ha^{-1}.year^{-1}. Meanwhile Butt et al (2005) showed that by 2030 in Mali cotton yields will increase up to an average of 6.2% under the projected climate change. In the second national communication of the Republic of Benin on climate change it is reported that across the agro-climatic zones in the country cotton yields will increase by about 2.2% to 6% by 2025 (MEHU 2011). Boko et al (2013) also reported that climate change may favour the production of cotton in Benin while Paeth et al (2008a) suggested that still in Benin slight reduction of the cotton yields up to -2% are to be experienced by 2025. Anyway, the production of cotton in Benin is found to be under the influence of climatic fluctuations. The developed crop model in this study revealed that the production of cotton is very sensitive to temperature in October (Figure 9.1).

As shown by Figure 9.1 changing rainfall patterns according to REMO RCM simulations will lead to slight reduction of cotton yields by 2050 whereas temperature increase will boost the production. But a close look at the temperature related predictors reveals that while assuming no changes of the mean air temperature in October the overall yields decrease. But the increase in the mean air temperature in October is able to strongly counteract the negative effects in the future from all other climatic predictors. Therefore the increase in cotton yields can be attributed to the increase in temperature in October. Though it is not of ease to explain physiological processes occurring in crop with a statistical crop model one can attempt here to suggest that temperature increases in October as projected by REMO climate model – the last month of the growing season of cotton in Benin– may favour the opening of the cotton bolls (i.e. the protective capsules) and the drying of the cotton fibre before the harvest.

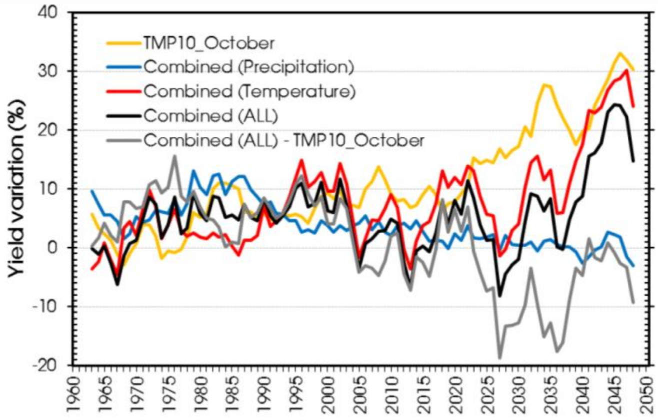


Figure 9.1: Separated and combined effects of precipitation and temperature on cotton production in Benin under changing climate conditions according to REMO (SRES A1B+LCC) simulations.

Temperature increase at the start and end of the growing season was reported to positively influence cotton yield by extending the time of the growth (Bange 2007). According to Reddy et al (2000) cotton fruit may survive temperature increases up to approximately 32°C. During the phenological phases from cotton plant emergence to the first flower bud formation (i.e. square) and from the square to flower the development rate increases with temperature increase up to an optimum of about 30°C and decreases thereafter. But from the flower to the open boll the development rate linearly increases with increasing temperature (Reddy et al 2000).

The differences between the magnitude of the crop yield projections in this study and the evidence in the literature are likely due to (1) the use of different baseline periods for the computation of the yield changes, (2) the use of different crop models/crop modelling approach and (3) climate model outputs driving the crop models (Roudier et al 2011). For example in their crop yield changes studies in Benin, Lawin et al (2013) used the global climate models CNRM-CM3, ECHAM 5, CSIRO Mark 3 and MIROC 3.2 and found that contrary to CSIRO Mark 3 and MIROC 3.2, precipitation in Benin by 2050 increased in CNRM-CM3 and ECHAM 5 whereas the four models agree well on the direction of changes in air temperature with an increase in the normal annual maximum temperature ranging from 1–1.5°C for MIROC 3.2 to 2.5–3.0°C for ECHAM 5. Additionally Challinor et al (2015) indicated that the spatial variability of future yield changes among countries in the same region could also be related to the heterogeneity in cropping intensity. These authors further suggested to take into account the variation in cropping intensity while spatially assessing climate change impacts on crop production.

It should also be noted that the outcomes of this study present just a national picture. Given the inhomogeneity in the spatial distribution of precipitation in Benin as in the whole tropical West Africa these outcomes may hide some disparities at sub-national levels. Lawin et al (2013) already indicated that in present-day and the future the production profiles of the crops grown in Benin is not homogenous. Similar results were also found by Tingem and Rivington (2009) in Cameroun.

- Relative contribution of precipitation and temperature changes to agricultural yield changes

Although there are a large number of interplaying factors in crop development and yield elaboration, identifying the greatest causal factor of the yield losses is important for a better targeting of the adaptation needs in agriculture (Mishra et al 2013). In this study the future mean yield changes were found to be more driven by temperature than precipitation. This is in accordance with findings from many scholars including Lobell and Burke (2008), Sultan et al (2013), Waha et al (2013b) and Bassu et al (2014). Robust estimations (based on 23 mechanistic crop models) from Bassu et al (2014) across different climatic environments representing the wide range of maize growing areas in the world suggested maize yield responses of -0.5 $Mg.Ha^{-1}$ per °C of temperature increase. West Africa is amongst the regions most vulnerable to temperature increases (Boko et al 2007). In this region temperature increases may lead to more than 20% decrease of maize yields (Waha et al 2013b). Lobell et al (2011b) revealed that in the past also temperature variation rather than precipitation had greatly influenced global crop production. Sultan et al (2013) stated that the probability of yield reductions is even higher in the sudanian region of West Africa including Benin than in the sahelian part due to the high sensitivity in the sudanian region to temperature changes as opposed to the sahelian part more prone to be sensitive to rainfall changes. Furthermore, they indicated that with warming above 2°C in the sudanian region of West Africa the induced negative influences of crop yields cannot be compensated by rainfall increases. Temperature regimes during the crop growing seasons in West Africa are reported to be already close to the upper limit of the optimal temperature range (20°C – 30°C) required for the majority of crops grown in the region (Singh et al 2013). As well, depending on the crops, warming above 29-32°C is often said to be very harmful to growth and reproductive processes (e.g. upper optimal limit of 29°C for maize, 30°C soybeans and 32°C for cotton) (Schlenker and Roberts 2009; Lobell et al 2011a). Other scholars also pointed to leading non-linear effects of temperature on agricultural production in Africa and suggested that each degree day experienced about the threshold of 30°C generally results in 1% loss of maize yields in optimal rainfed conditions and 1.7% in drought conditions (Lobell et al 2011a). For a crop like maize the reproductive phase is said to be quite sensitive to heat stress (Dupuis and Dumas 1990; Cairns et al 2013), with delay of the emergence of the female reproductive tissues (i.e. silks) when the increases in temperature occur early at that phase (Cicchino et al 2010), and the quantity and viability of the produced pollen decreasing also with higher temperatures (Schoper et al 1986). But, contrary to the outcomes of this study and those of the previously cited scholars Cooper et al (2008) reported that the detrimental effects of the reduction in precipitation on African agricultural outputs will be more important than those of the increasing air temperature in case current agricultural practices remained unchanged. But Waha et al (2013) showed that in West Africa (below 13°N) the effects of temperature increases on maize production prevail over those of the changes in precipitation patterns, thus suggesting that temperature will be the major limiting factor for agricultural production in the Guinean and Sudanian parts of West

Africa. Waha et al (2013) further showed that these effects of temperature and precipitation are variable in space across Africa. In Western Africa (below 13°N), central Africa and Eastern Africa, the changes in the wet season precipitation will drive between -3% and +3% of the maize yield changes during the time period 2056-2065 whereas temperature increases will lead to between 3% and 30% reductions (Waha et al 2013b). Meanwhile in the Sahel countries, in southern Africa and parts of the Eastern Africa, the negative effects of precipitation changes are projected to be stronger than those of temperature (Waha et al 2013b). The production of maize is very sensitive to water deficit from the physiological stage 10-12 leaves to the dough grain stage (Sobrado 1986; Mansouri-Far et al 2010; Agbossou et al 2012), and in particular during flowering, and the grain formation and filling phases (Agbossou et al 2012). As reported by Agbossou et al (2012), Algans and Desvignes (1983) stated that during those physiological stages water stress causes reductions in the number of grains per ear, ear number and individual grain weight and thus yield reductions. Akponikpè (1999) has already shown yield reductions in southern Benin during the period 1971-1990 compared to 1950-1970 as the result of the drought that occurred across West Africa. But in general, with respect to most crops, many crop simulation studies indicated that with the projected future climates globally and in West Africa in particular the major side effects on the various cropping systems arise from temperature increases which in turn increase crop evapotranspiration as well as the losses of assimilates through the maintenance of crop respiration which also increase with temperature, and drive the reduction of the length the cropping cycles, thus leading to crop yield failure (Salack 2006a; Sultan et al 2013).

- Effects of land cover change on agricultural yield changes

Major driving forces of land use and land cover changes in West Africa are said to be population pressure, road network and legal constraints for the protection of nature (Igue et al 2000; Braimoh and Vlek 2005; Menz et al 2010; Gaiser et al 2011). Considering different land use and land cover scenarios, Gaiser et al (2011) proved that maize yields in Benin steadily decrease with decreasing fallow-cropland ratio up to an average of 24% reductions. Gaiser et al (2011) further indicated that in the coming decades the detrimental effects of land use and land cover changes on maize production in Benin will be as much as those from climate change due to more GHG emissions. The "Mémento de l'agronome" reported that along the yam belt from Nigeria to Côte d'Ivoire in the savannah zones of West Africa every year forests and woodlands were cleared by slash-and-burn technique and used for the production of yams (shifting cultivation) that is highly demanding in nutrients so as to meet the soil fertility level required for yams (Caburet et al 2002). Caburet et al (2002) further stated that the increase in the production volume of yams is positively correlated with the expansion of croplands used for that production. Although the results of this study suggested that the on-going land cover changes will boost the production of cotton and yams it should be questioned whether further expansion of their croplands is required. The production of cotton is currently the first source of export earnings in Benin (MAEP 2011). Yams is an alimentary crop fully integrated in the social-life in central and northern Benin and well-appreciated throughout Benin for its organoleptic qualities and nutritional values (Hounhouigan et al 2003). Hence farmers are accustomed to them. As these crops are important in Benin should extensive cultivation of cotton and yams continue at the expense of the other crops? There are good reasons to believe that considerable expansion of the agricultural lands in Benin and the whole sub-Saharan Africa may have detrimental effects on regional climate systems as it will enhance the increase in temperature and the long drought tendency that are being experienced (Paeth et al 2009). In fact many scholars have already shown that land use and land cover changes (deforestation and desertification) in tropical West Africa can alter the regional climate system, impact on the global climate system through a kind of vegetation-driven teleconnections, and cause climate change (Feddema et al 2005b; Abiodun et al 2008; Verburg et al 2011; Deng et al 2013; Mahmood et al 2014). Although their simulations did not allow for vegetation feedback on climate, Paeth et al (2009) suggested that land use and land cover changes are directly responsible of about 35% of the future increase in temperature in sub-Saharan Africa in general and almost the entire decrease in precipitation, except in the tropical part of Western Africa where it is found to drive two-third of the drying tendency. Thus land use and land cover changes are greatly responsible for the projected future climate change across sub-Saharan Africa. But most regional climate model projections in West Africa did not account for the transient effects of land cover/land use change (Paeth and Thamm 2007; Paeth et al 2009; Paeth et al 2011b; Collins 2011; Diallo et al 2012). As combined effects of land degradation and GHG forcing according to SRES A1B scenario, it was projected until 2050 additional warming in the range of 1.5°C and 3°C in tropical West Africa (Paeth et al 2009) and decreasing precipitation totals ranging between 100 mm in the southern part of the Sahel zone and 500 mm in the central Congo basin (i.e. 20-25% reduction in total amounts relative to the present-day precipitation climatology) (Paeth et al 2009). In a similar way, Alo and Wang (2010) asynchronously coupled a dynamic vegetation model (CLM-DGVM) to a regional climate model (RegCM3 nested in the global climate model CCSM3) to examine the contribution of land cover and land use changes on future climate change in West Africa as Moore et al (2014) did also in Eastern Africa. Their study concluded that due to the feedback effect from vegetation it is expected 2% decrease of June to August precipitation over the Guinean Coast and 23% increase over the Sahel by 2084-2093; otherwise 5% decrease is projected in both regions without vegetation feedback (Alo and Wang 2010). As West African agriculture is dominantly rainfed more reduction of precipitation amounts and increase in temperature in the future due to this land degradation and GHG emissions will pose a serious threat to agriculture in general. Challinor et al (2015) suggested that accounting for land use changes is important for the assessment of crop productivity. In the same way, at decadal time scales and in response to future climate change there can be shift in the distribution of some plant species or conversion from a given land cover class to another one (Olesen and Bindi 2002; Challinor et al 2015). By acting as cause of and response to climate change, land cover/land use change may greatly influence the changes in crop production (Challinor et al 2015). Moore et al (2011) indicated that in magnitude the effects of land use/land cover changes on crop production can be as big as that of GHG emissions. Feeding the growing population in Benin may become problematic as the smallholder farmers will have to struggle to grow in water-limiting environments with heat stress increasing crop evapotranspiration. As well, further substantial expansion of croplands will severely endanger the remaining natural ecosystems, thus jeopardizing their biodiversity and the multiple ecosystem services they provide (Hillel and Rosenzweig 2013). Hence, a compromise must be found in the benefit of both the natural ecosystems to conserve for the current and future generations and the agricultural production to increase. Sustainable intensification in the various cropping systems could help maintain and even increase the food production level so as to meet the food requirements for the growing population (Hillel and Rosenzweig 2013). Many authors suggested that conservation agriculture is the best option in face of the growing challenges (Jalloh et al 2013a; Mason et al 2015). Conservation of the remaining forest and savannah ecosystems, afforestation and forest restoration are also crucial across Africa to mitigate the effects of the projected climate change (Paeth et al 2009; Abiodun et al 2012; Sinare and Gordon 2015). With a set of regional climate simulations of various reforestation options in the Guinean, Sudanian and Sahel zones of West Africa, Abiodun et al (2012) suggested that in tropical West Africa and during the time period 2031-2050 reforestation may reduce the projected warming and drying tendencies over the reforested zones while enhancing their increase outside the reforested zones. Therefore mutual agreement among the countries in the region is crucial for strategic reforestation (Abiodun et al 2012).

- Sensitivity analysis

Statistical modelling of crop yields is very sensitive to the training datasets used as well as the assumptions made on the non-climatic effects. As shown by Figure 9.2 for the rice crop model training the crop model with datasets on different time periods results in yield projections that are controversial even on the direction of yield changes.

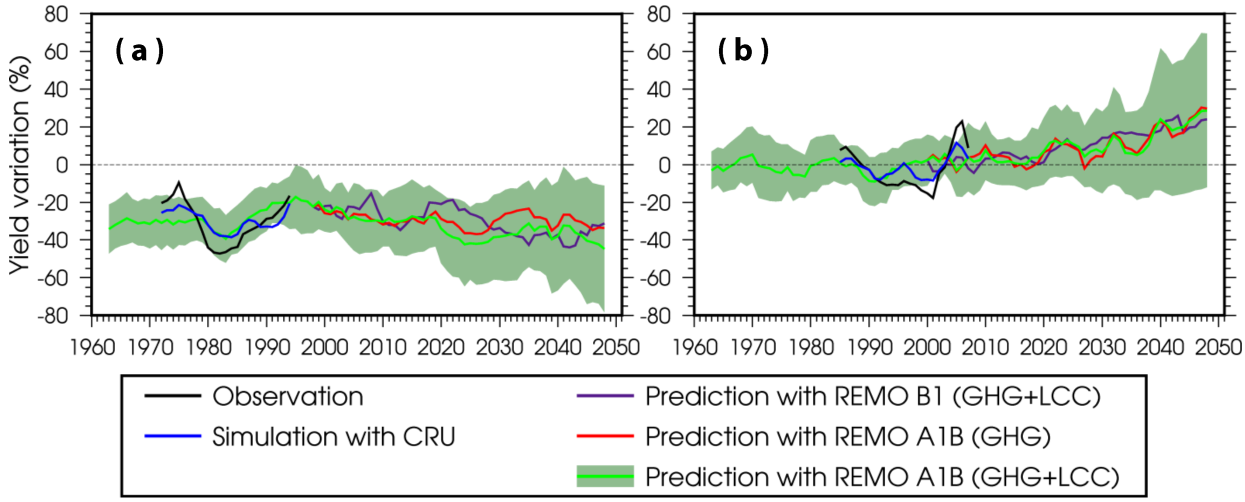


Figure 9.2: Sensitivity of the rice crop models to the training datasets.

(a) The crop models were trained with historical yield data for the time period 1970-1992; Performance of the average model: R^2 = 58.56%, BSS = 0.33.

(b) The crop models were trained with historical yield data for the time period 1987-2009; Performance of the average model: R^2 = 58.89%, BSS = 0.34. Note that in both (a) and (b) the observational climate and yield datasets were linearly de-trended over the training period before the development of the crop models.

As introduced early statistical crop modelling is also sensitive to the assumptions made on the non-climatic effects (e.g. improvement in crop production technology, farm management, pests and diseases effects) and thus the methods used to remove those effects from the training datasets (Lobell and Field 2007; Osborne and Wheeler 2013). As shown in Figure 9.3 for the rice crop model while removing a quadratic trend from the observed yield dataset in (b) compared with (a) where a linear trend is removed from the same yield dataset the uncertainties in the projected yield changes are considerably reduced. Observation of the black lines (i.e. residuals lines) in Figure 9.3 a & b shows greater inconsistency between the two yield de-trending methodologies. After removing a linear trend from the training yield dataset there is still a persistent non-linear trend as evidenced by the black line in Figure 9.3a. After suppression of all the trend effects the individual rice crop models agreed well on the direction and magnitude of changes in (b) than they do in (a). Thus in the case of rice here removing linear trend from the training datasets appears to be unsuitable. Osborne and Wheeler (2013) already pointed to the unsuitability of the linear trend approximation to remove the technology trend from the observed rice yield time series in many rice growing countries. Linear, quadratic, cubic trends and first-difference method (i.e. difference from one year to the next) are commonly referred to while removing technology trend, and the residuals are examined for further analysis (Lobell and Field 2007; Osborne and Wheeler 2013). As shown in their crop-country combinations analysis (Osborne and Wheeler 2013) the linear trend applied here in the four previous Chapters was found unsuitable in some cases, the cubic approximation was often exactly alike the quadratic trend and thus not preferable in those cases. The first-difference method appears also to be a good approximation as regression using first-difference time series assumes that changes in yields can be driven by only changes in climate; but its use can be restricted in case the absolute values of the variables involved in the regression are required (Osborne and Wheeler 2013).

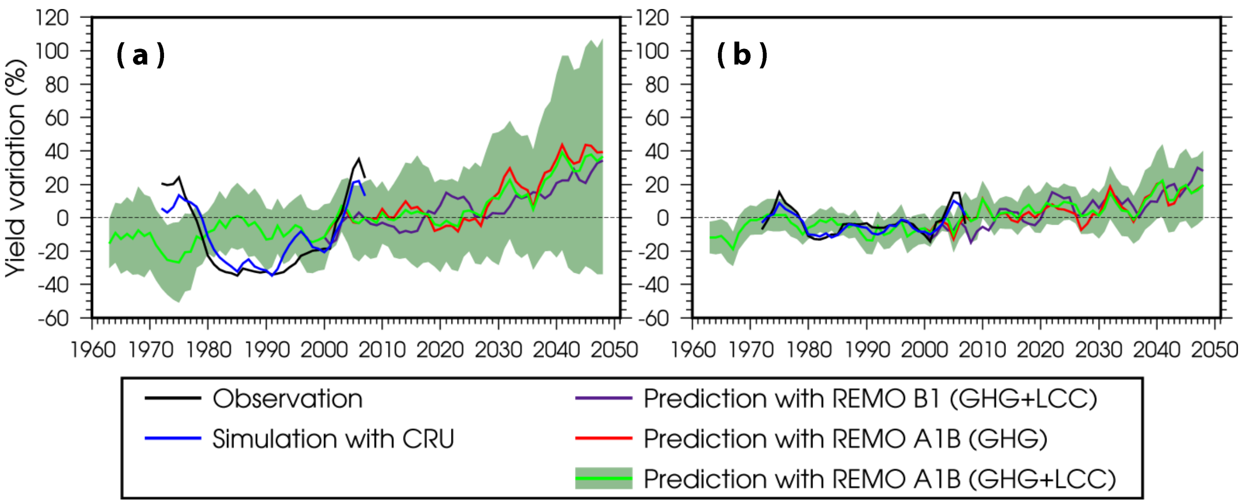


Figure 9.3: Sensitivity of the rice crop models to the method used to remove long-term trend from the observed yield dataset.

(a) First-order polynomial trend (linear trend) was removed from the observed yield dataset; Performance of the average model: R^2 = 77.39%, BSS = 0.52.

(b) Second-order polynomial trend was removed from the observed yield dataset; Performance of the average model: R^2 = 59.68%, BSS = 0.36. Note that in both (a) and (b) only linear trends were removed from the observational climate datasets.

9.2 Uncertainties and limitations to knowledge

Every modelling study has its limitations. Therefore the methodological approaches used in this study have also got some limitations which should be recognised. As the results of this study are purely based on statistical crop modelling, the adaptation strategies already developed and being applied by farmers were not considered. Consideration of those adaptation options could improve the attainable yields under climate change. With a set of adaptation options, Butt et al

(2005) showed that mixed crops and heat tolerant varieties can help improve agricultural production in a context of changing climate.

Rurinda et al (2014) reported that in many projections of yield changes under changing climate conditions the impact of nutrients limitation is ignored. In West African agriculture in general less investment is put in agricultural inputs like chemical fertilizers. Simulation studies revealed that with rational use of fertilizers in the production the crop yield losses in West Africa could be reduced up to -5% (Roudier et al 2011).

Crop models are widely used to predict the effects of changes in environmental variables (e.g. precipitation, temperature, relative humidity) on crop growth, development and yields (Semenov and Porter 1995). While using the crop models it must be noted that the processes occurring in the plants are connected to the environment via a mixture of linear and non-linear responses (Semenov and Porter 1995). As pointed out by Semenov and Porter (1995), although plant development processes generally show positive linear responses, there are conditions for which the responses can be inversed and thus the rate of a process may decline. Then this may complicate statistical predictions (Hansen et al 2006). Per example, a non-linear relationship is proven between amount of precipitation and the water-use efficiency of plants (Semenov and Porter 1995). Average amounts of precipitation are used relatively more efficiently by plants than larger amounts because of rapid movement of excess water to deep and unavailable layers in the soil (Keulen and Wolf 1986; Semenov and Porter 1995). Many studies have even already pointed to the non-linear effects of temperature on agricultural production (Rötter and Van De Geijn 1999; Schlenker and Roberts 2006; Lobell et al 2011a). Thus researchers investigating the impacts of past and future climate change on agricultural production should bear this in mind.

Extreme climate and weather shocks are also of great relevance and often not considered in agricultural impacts predictions (Knox et al 2012). These extreme weather events, such as floods, drought and extreme heat stress can greatly influence crop development (Katz and Brown 1992; Semenov and Porter 1995; Wheeler et al 2000; Knox et al 2012) and lead to higher yield failure (Deryng et al 2014). West Africa has experienced pronounced drought spells during the 1970s and 1980s with severe agricultural consequences (Benson and Clay 1998; Nicholson et al 2000; Nicholson 2001; Le Barbé et al 2002; Nicholson 2013). Recently the region was also faced with widespread flooding in 2007 caused by unusual and abundant rainfall events with loss of human lives and severe economic consequences among which destruction of crops and livestock, homes, and infrastructures (Levinson and Lawrimore 2008; Braman 2009; Paeth et al 2011a; Tall et al 2012; Braman et al 2013). Thus future climate extreme events can also be very challenging for the West African smallholder farmers (Rosenzweig et al 2001; Tingem and Rivington 2009). Therefore in coupling climate information with crop models the changes in the intra-seasonal variability of the climatic variables are as important as their mean. Incorporating this detailed information in the crop models will lead to a better transposition of the distribution of weather sequences into a distribution of dry matter and attainable yield (Semenov and Porter 1995). For example, Semenov and Porter (1995) reported that high and low temperatures decrease the production of dry matter in a crop plant and the extremes can completely lay off the production. As well water stress immediately before flowering can cause sterility of the pollen and decrease in grain yield (Saini and Aspinall 1981; Semenov and Porter 1995). They further hypothesise, based on sensitivity experiments, that increasing temperature variability may decrease grain yield more drastically than changes in mean temperature (Semenov and Porter 1995).

Linking impact modelling and adaptation planning is very challenging. Addressing this issue of marrying impacts and adaptation research, Johnston et al (2013) pointed to some options in the forestry sector in Canada to strengthen the collaboration between researchers, stakeholders and practitioners for a better adaptation to the looming climate change. This need of collaborative decision-making for better adaptation holds for the agricultural sector as well. Stakeholders and practitioners across sectors often argue that the uncertainty about future climate conditions limit the adaptation planning because they always want to have a clear view of the future (Johnston et al 2013). But as it is still not possible to accurately predict the future it would be better to follow approaches like the no-regrets option and develop policy and management options that are robust to a large range of future conditions (Johnston et al 2013).

As extensively explained above, the crop modelling approach, the training and validation datasets, the multi-model combination approach and the driven climate model have a pronounced effects on the crop yield changes reported in this study. Thus more reliable analysis of sign and magnitudes of future yield changes required careful handling of these uncertainty issues (Rötter et al 2012; Mishra et al 2013). The uncertainty in future climate projections is to be taken into account to accurately predict the responses from the agricultural systems and set adaptation priorities (Tao et al 2009a; Tao et al 2009b; Rötter et al 2011; Cairns et al 2013; Rötter 2014; Bassu et al 2014). For example CNRM-CM3 and ECHAM 5 projected increased precipitation for some parts and no significant decrease in the other parts of the Republic of Benin while decreasing precipitation were projected for most parts of the country in the CSIRO model and southern parts in the MIROC 3.2 model (Lawin et al 2013). Regarding temperature although state-of-the-art climate models agree well on the direction of changes there are still inconsistency in the magnitude of change. For example, assuming future changes according to SRES A1B scenario MIROC 3.2 projected 1°–1.5°C increase in temperature while CNRM-CM3 showed an increase in the range of 2.0°–2.5°C in the Republic of Benin. Meanwhile CSIRO Mark 3 projected an increase 1.5°–2.0°C of temperature in most regions of Benin while similarly to CNRM-CM3, ECHAM 5 shows a rise of 2.0°–2.5°C in the northern parts of the country and 1.5°–2.0°C for the rest of the country similar to the CSIRO model (Lawin et al 2013). Despite the great progress, state-of the-art regional climate modelling in sub-Saharan Africa is also still tainted by large disagreements among CGCMs and RCMs on the magnitude of changes in precipitation and temperature, and even divergence on the sign of the changes in precipitation especially in West Africa. In fact climate model outputs about future climate change are not provided with any information about the likelihood of the occurrence of the projections (Cubasch et al 2001; Haensler et al 2013). After Dessai and Hulme (2007) and Hallegatte (2009) Haensler et al (2013) also argue that in the definition of adaptation strategies in face of future climate change robustness of the climate change information is necessary to better inform and accelerate the decision process. Therefore uncertainties in the future climate signal are to be transplanted into the crop models by driven them with a set of sufficiently large and independent multi-climate models ensemble, run themselves with multiple scenarios in order to come up with a clear robust analysis on the range of impacts (Lobell et al 2006; Rötter et al 2012; Gosling 2013; Mishra et al 2013). Multiple crop models forced with a single climate model or multiple climate models should also be used to assess the uncertainties owing to differences in the structure and parameterisations of the crop models (Ceglar and Kajfež-Bogataj 2012; Gosling 2013). Even for each crop model sensitivity analysis of the model parameters should be performed to account for the uncertainty in the crop model parameters (Tao et al 2009b) as done also by Ceglar et al (2011) who implemented a Bayesian calibration of the WOFOST crop model. The inter-crop models comparison has already started in the framework of the Agricultural Model Intercomparison and Improvement Project (AgMIP), with sub-Saharan Africa holding five multi-disciplinary teams among which the climate change impacts on West Africa Agriculture team (CIWARA) focusing also on how climate change leads to changes in the food production systems and thus food insecurity (Rosenzweig et al 2012; Rosenzweig et al 2013). In general the uncertainties in the response of crops to climate change are less assessed while compared with those in the climate change signals from coupled GCMs and RCMs (Murphy et al 2004; Lobell et al 2006; Gosling 2013).

As well, the effects of atmospheric CO_2 fertilization could not be accounted for in the statistical crop models. C3, C4 and CAM plants are said to be diversely sensitive to temperature and CO_2 increases (Larcher 1995; Rötter and Van De Geijn 1999; Larcher 2003; Salack 2006b). Many studies have reported a positive effect of higher atmospheric CO_2 concentration on crop photosynthesis, vegetative growth (Tubiello et al 2007; Kaufmann et al 2008; Roudier et al 2011) and thus crop yield formation. As shown in the agronomist and biologist literature atmospheric CO_2 enrichment will stimulate photosynthesis in C3 plants such as rice and thus result in yields increase (Rötter and Van De Geijn 1999; Larcher 2003; Cairns et al 2013; Hussain et al 2013). In the C4 plants (e.g. maize, sorghum) this increase in atmospheric CO_2 concentration will have no effects on photosynthesis as saturation at optimum is reached at the current concentration levels (Rötter and Van De Geijn 1999; Leakey et al 2009; Cairns et al 2013). Contrary to that Bassu et al (2014) reported doubling atmospheric CO_2 concentrations relative to the current baseline resulted in an average of 7.5% maize yield gain. Bassu et al (2014) further indicated that the effects of atmospheric CO_2 fertilization is still controversial since per example across 23 mechanistic maize-crop models some models projected increases in yields in response to doubling atmospheric CO_2 concentrations from 360 to 720 μmol^{-1} while others return opposite results. Thus it might be possible that crop growth processes such as the photosynthesis and respiration are still not correctly integrated in all process-based crop models in such a way that accurate responses to elevated CO_2 concentrations could be obtained (Porter and Semenov 2005; Soussana et al 2010; Webber et al 2014; Bassu et al 2014). Due to this large uncertainty across crop models, more research is still needed to shed light on the real state of the responses of the crop growth processes in CAM, C3 and C4 plants to increase in atmospheric CO_2 concentrations.

As well, many studies often fail to consider in their crop yield projections the impacts of climate change on weeds and the population of pests and plant parasites. With climate change the incidence of plant parasites, pests and diseases in the cropping systems may increase in range and severity, resulting then in an additional threat to the production (i.e. more pests and disease attacks) (Petzoldt and Seaman 2006; Rao et al 2006; Ghini et al 2011; Fand et al 2012; Knox et al 2012; Paterson et al 2013; Fand et al 2014). In this context diversification of the production systems can be seen as a valuable way to increase both the production and the resilience of the agricultural ecosystems (Van Staveren and Stoop 1985; Lin 2011; Rurinda et al 2014). Tropical and subtropical regions are even said to be more prone to these pest outbreaks in response to climate change as conditions there are well-suited for multiplication and food availability (Fand et al 2014).

Another source of uncertainty not often considered in the crop modelling approaches is regarding agricultural practices like mixed cropping (White et al 2011). Often practiced across cropping systems in West Africa, intercrops and crop rotations are understudied in agricultural impacts assessment (Challinor et al 2007; White et al 2011; Webber et al 2014).

In view of all these limitations, the potential effects of future climate change as presented in this study, although robust, should be considered as projections and not certainties. Future modelling efforts should address all these sources of uncertainty and their interactions to improve preparedness to climate change and its effects, and better agricultural risk management.

9.3 Possible avenues to offset negative climate change impacts in agriculture

In the scientific literature devoted to climate change adaptation and mitigation several studies have focused on the needs and options for adaptation to climate change in agriculture and ensure food security across sub-Saharan Africa. The reported strategies hold also for the Beninese agricultural sector in the face of future climate change. Adaptation of the agricultural sector to climate change will pass by search for transdisciplinary solutions (Howden et al 2007; Cairns et al 2013) to reduce the negative impacts of climate change while enhancing the positive influences. With the recent progresses in biotechnology, high-yielding crop cultivars are already available. But improvement of the crop cultivars or development of new germplasm with tolerance to higher temperatures, drought stress or both stresses is needed to sustain food production under future climate change conditions (Thornton et al 2009; Burke et al 2009; Jalloh et al 2013a; Singh et al 2013; Cairns et al 2013). Farmers should later be fostered to use the new crop varieties more suited to the future climate conditions (Cairns et al 2013). As the development of the new climate-adapted germplasm takes times, in the meantime many studies have pointed to some fundamental revision in the cropping systems that can help offset the negative impacts of climate change in agriculture. Optimal management of the cropping systems (e.g. agroforestry practices, mulching, use of cover plants, intensification/diversification of the cropping systems, good selection of crops/crop varieties, multiple cropping systems) (Waha et al 2013a; Mccord et al 2015), optimal choices of the sowing/planting dates (Allé et al 2014; Yegbemey et al 2014), better agricultural water management (e.g. supplemental irrigation, rainwater harvesting) (Pandey et al 2003; Oweis and Hachum 2006; Vohland and Barry 2009), as well as adoption of other appropriate climate-smart agricultural practices (Branca et al 2011a; Branca et al 2011b) and conservation agriculture with minimum or no-tillage (Bayala et al 2012; Speranza 2013; Corbeels et al 2014) are often cited as possible alternatives. Allé et al (2014) indicated that both the sowing dates and the seed varieties (short cycle or long cycle crop varieties) should be optimally selected in accordance with the onset of the rainy season and its length. In addition, Regh et al (2014) indicated that in Benin rational use of fertilisers and optimal choice of the sowing dates (i.e. after an accumulated rainfall of significantly higher than 100 mm) of the annual crops like maize can stabilize agricultural production. Simulation results from Fosu-Mensah et al (2012) confirm the benefit from the use of inorganic fertilisers (Nitrogen and Phosphorus fertilizers) in the cropping systems while Branca et al (2013) reminded the benefit of the use of organic fertilizers (e.g. green manure, compost).

Due to the large effects of the land cover/land use changes in the reduction of precipitation amounts, increase in temperature in West Africa (Paeth et al 2009) and the drop of crop yields it is urgent for decision makers to take effective measures to limit the on-going land degradation processes and other anthropogenic actions causing temperature increases and changes in precipitation patterns. Emphasis is again to be put on soil organic carbon sequestration for which benefit to global and regional climate systems and food production is largely demonstrated (Sanchez 2000; Lal 2004; Ghimire et al 2011; Branca et al 2013).

To tackle the negative impacts of climate change in agriculture, it is also necessary to develop seasonal climate predictions and disseminate the pertinent outputs in an easily understandable way (Hansen 2002; Ingram et al 2002; Amissah-Arthur 2003; Wilby et al 2009; Egbule and Agwu 2013; Fujisawa et al 2013; Svoboda 2013), and through the appropriate communication channels (e.g. local media, extension services) (Vogel and Brien 2006) to help farmers adapt their crop calendar (e.g. selection of the optimal timing for sowing/planting) and also select more appropriate adaptation strategies (e.g. timing for irrigation, sowing/planting of heat tolerant or drought resistant crop varieties). Such predictions in advance of the weather patterns (seasonal climate forecasts) could thus benefit the development of early warning systems in agriculture (Genesio et al 2011) that is highly required for preparedness and better climate risk management in agriculture. These climate forecasts can also greatly assist the decision-making process for a better adaptation to climate change. In southern Nigeria, Iwuchukwu and Udoye (2014) already reported that the pineapple farmers pointed to the prediction of the onset of rainfall and adaptation strategies as their information needs on climate change. More robust assessments of the potential impacts of climate change taking into account the uncertainties in the economic assumptions made, the climate models, the crop models, and considering also the adaptation options being applied are required to better assist the adaptation policy-making process. In the same vein, it is still necessary to stress out the urgent need to strengthen collaboration between the communities of climate modellers, impact modellers, policy-makers and farmers (e.g. opinion leaders) to ensure appropriateness of the information delivered at each step and a move toward an effective and sustainable adaptation of the food production systems to climate change.

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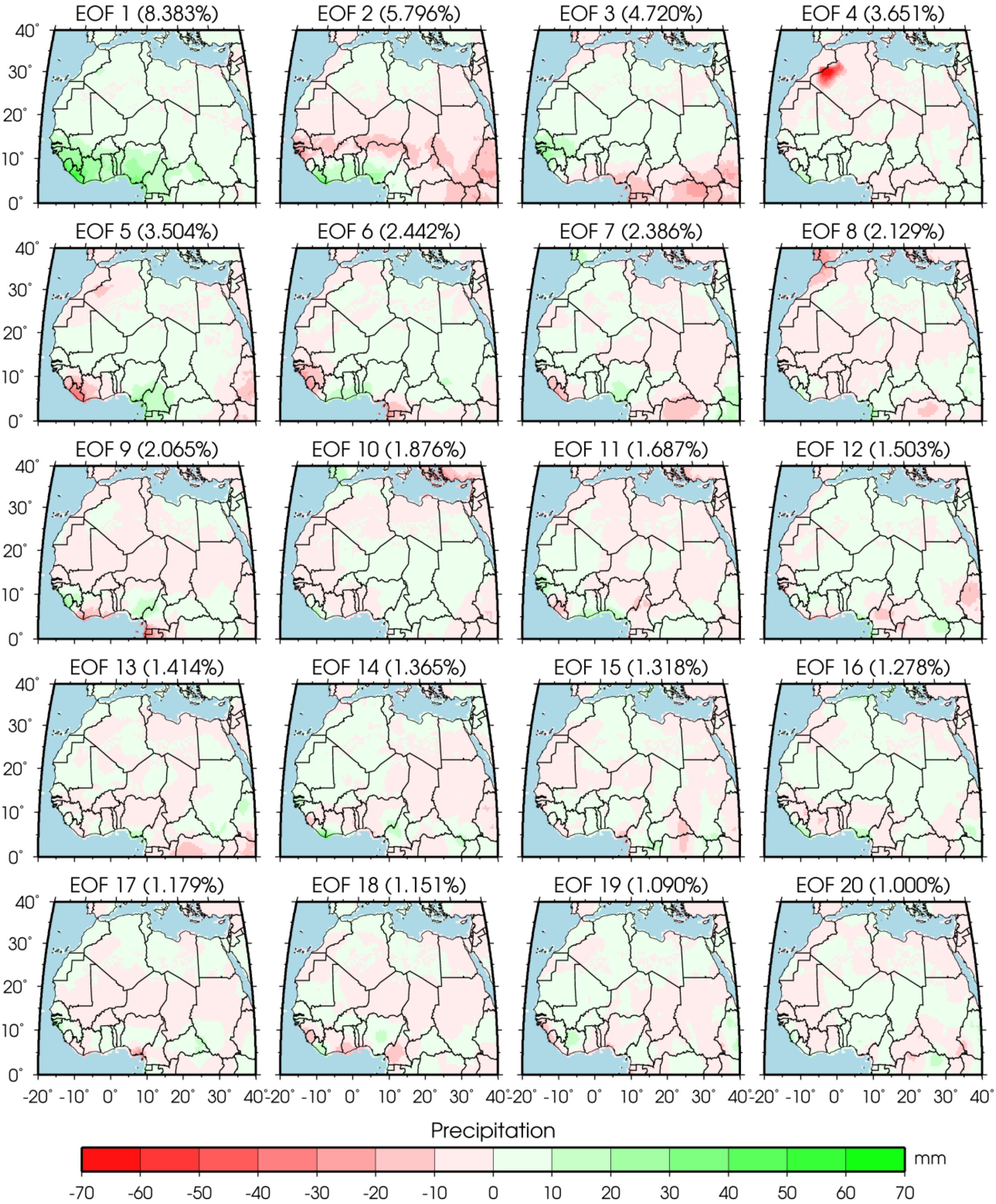
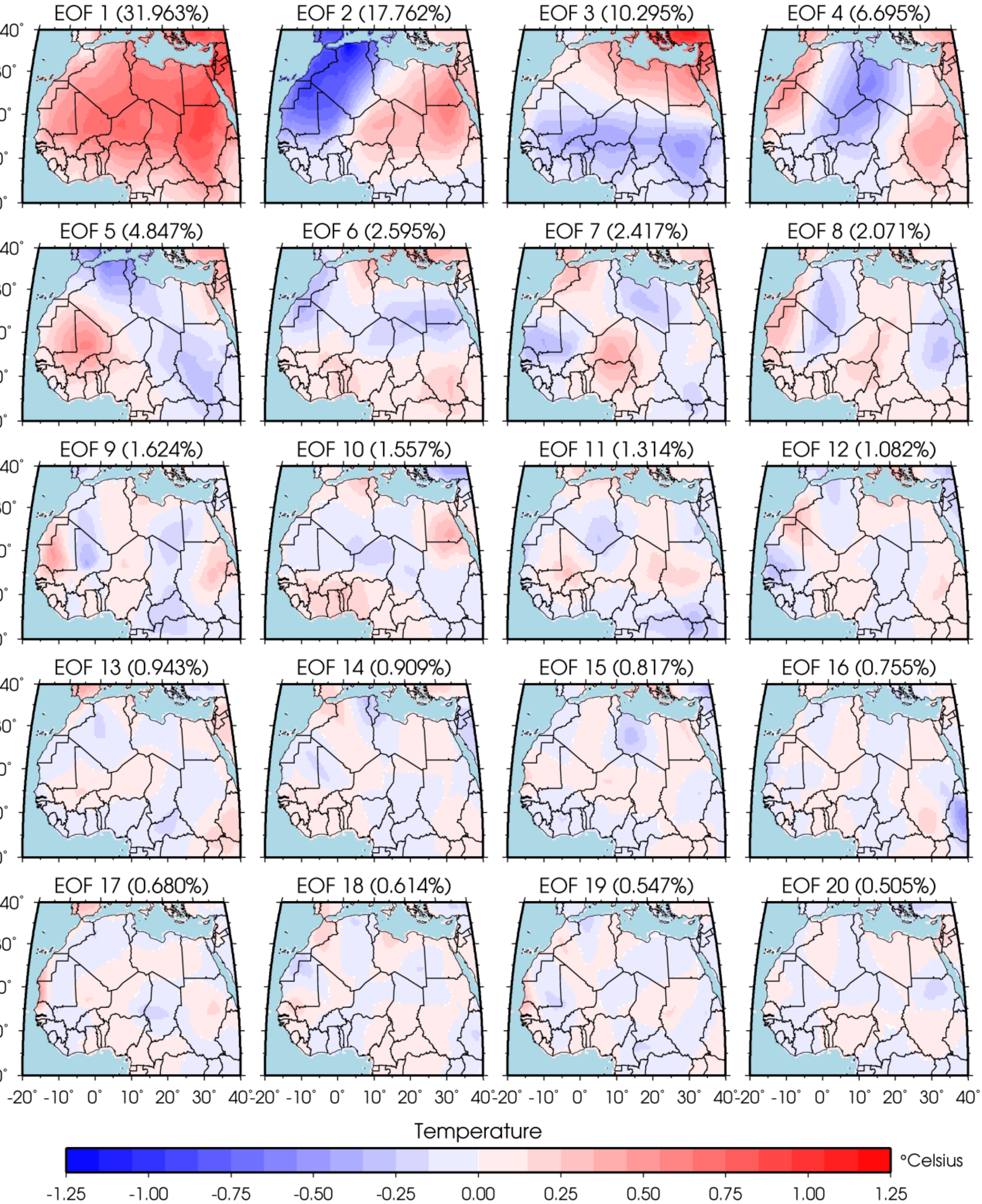
APPENDICES

Appendix A : Map of the patterns of the leading 20 EOFs of Precipitation



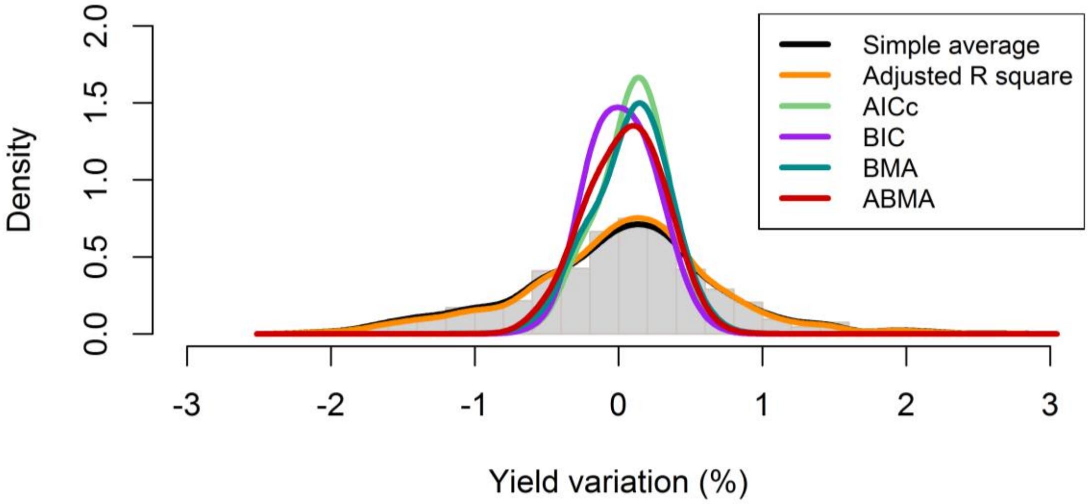
Appendix B : Map of the patterns of the leading 20 EOFs of mean near-surface air temperature.



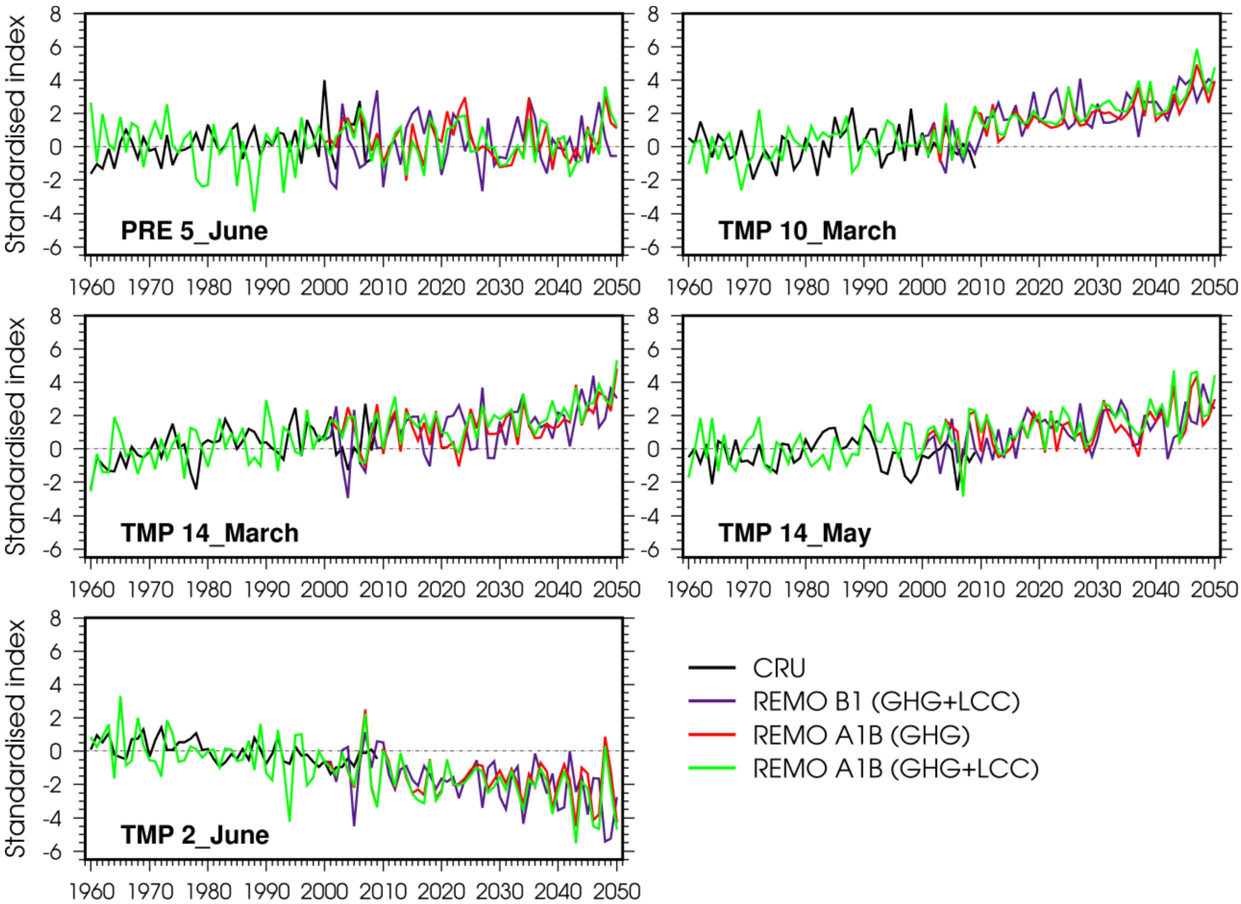
Appendix C: Estimated partial regression parameters for the statistical pineapple crop models. The 95% confidence intervals of the regression parameters are given into brackets.

Partial regression parameters	Multi-model combination techniques					
	Simple average	Adjusted R square	AICc	BIC	BMA	ABMA
β_0 (Intercept)	-0.001 (-0.138 – 0.136)	0.001 (-0.130 – 0.131)	0.009 (-0.033 – 0.051)	0.003 (-0.039 – 0.044)	0.008 (-0.041 – 0.057)	0.004 (-0.045 – 0.054)
β_1 (PRE 1_March_1)	0.302 (-0.463 – 1.068)	0.252 (-0.481 – 0.985)	0.000 (-0.017 – 0.016)	-0.087 (-0.342 – 0.169)	-0.006 (-0.070 – 0.058)	-0.060 (-0.263 – 0.143)
β_2 (TMP 1_April_1)	-0.126 (-0.432 – 0.181)	-0.142 (-0.455 – 0.171)	-0.301 (-0.358 – -0.245)	-0.379 (-0.618 – -0.140)	-0.299 (-0.382 – -0.216)	-0.343 (-0.540 – -0.146)
β_3 (TMP 6_October_1)	-0.256 (-0.716 – 0.203)	-0.284 (-0.737 – 0.168)	-0.463 (-0.505 – -0.421)	-0.503 (-0.634 – -0.373)	-0.463 (-0.525 – -0.401)	-0.489 (-0.611 – -0.367)
β_4 (TMP 10_June_1)	0.013 (-0.072 – 0.097)	0.014 (-0.074 – 0.101)	0.000 (-0.006 – 0.006)	0.061 (-0.141 – 0.264)	0.001 (-0.021 – 0.023)	0.028 (-0.114 – 0.170)
β_5 (TMP 13_April_1)	0.049 (-0.196 – 0.294)	0.050 (-0.198 – 0.298)	0.001 (-0.023 – 0.024)	-0.086 (-0.387 – 0.215)	0.005 (-0.057 – 0.067)	-0.030 (-0.258 – 0.198)
β_6 (TMP 15_June_1)	0.216 (-0.183 – 0.614)	0.237 (-0.155 – 0.629)	0.358 (0.289 – 0.427)	0.429 (0.216 – 0.642)	0.360 (0.275 – 0.445)	0.402 (0.227 – 0.577)
β_7 (TMP 10_July_1)	0.089 (-0.173 – 0.351)	0.098 (-0.169 – 0.366)	0.191 (0.108 – 0.275)	0.270 (0.017 – 0.524)	0.192 (0.079 – 0.304)	0.234 (0.013 – 0.454)
β_8 (PRE 13_February_2)	0.047 (-0.253 – 0.346)	0.045 (-0.256 – 0.345)	0.000 (-0.018 – 0.017)	-0.119 (-0.471 – 0.233)	-0.003 (-0.074 – 0.068)	-0.067 (-0.348 – 0.214)
β_9 (TMP 9_March_1)	-0.060 (-0.318 – 0.198)	-0.057 (-0.309 – 0.195)	0.000 (-0.003 – 0.003)	0.001 (-0.013 – 0.014)	0.000 (-0.017 – 0.017)	0.003 (-0.039 – 0.046)

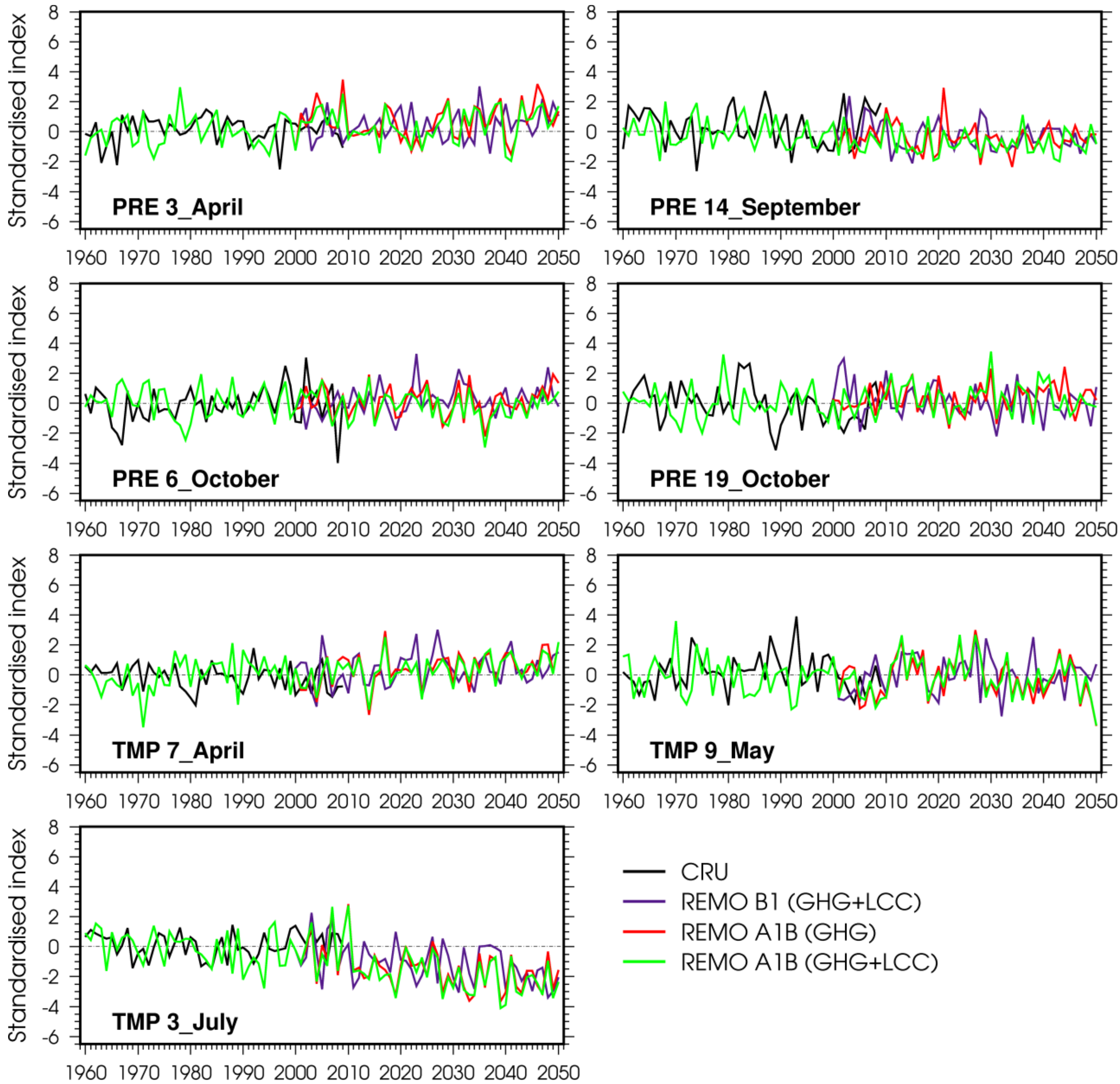
Appendix D: Uncertainty in the statistical pineapple crop models following different multi-model combination methods.



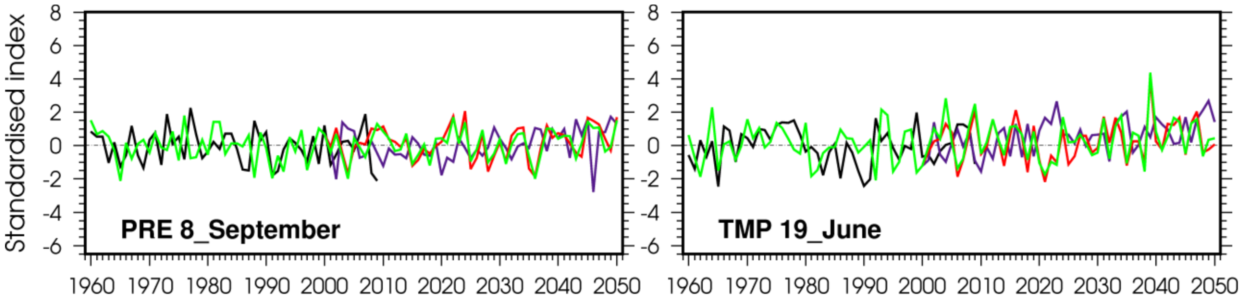
Appendix E: Temporal evolution of the current and future time series of the most important climatic factors for the prediction of cowpeas production in Benin



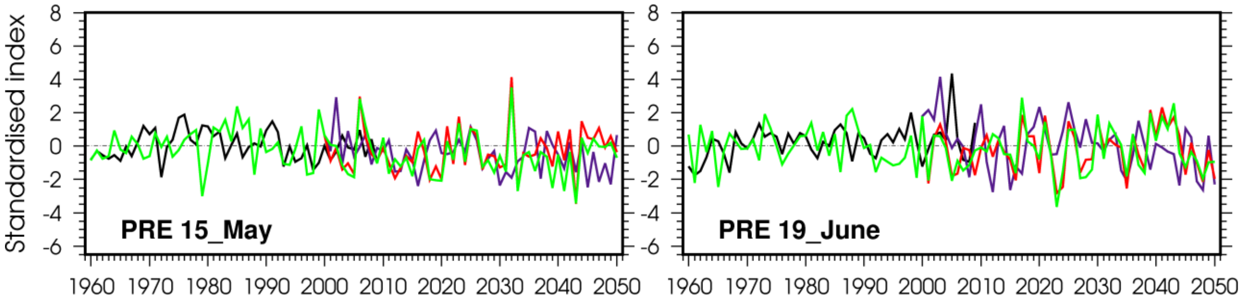
Appendix F: Temporal evolution of the current and future time series of the most important climatic factors for the prediction of maize production in Benin.



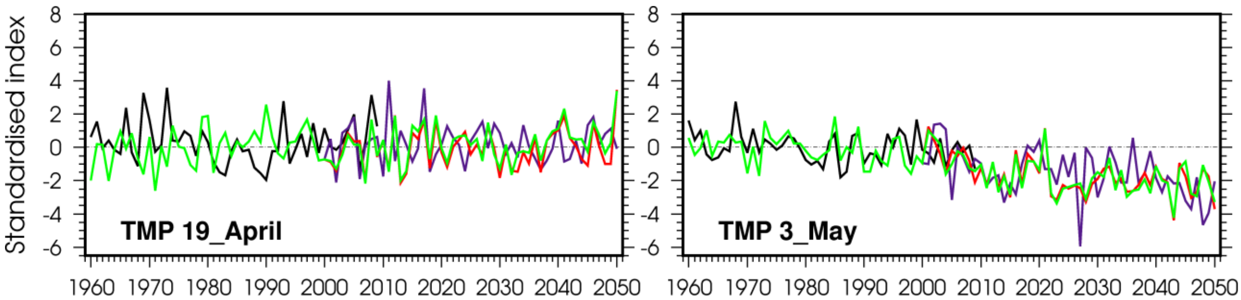
Appendix G: Temporal evolution of the current and future time series of the most important climatic factors for the prediction of rice production in Benin.



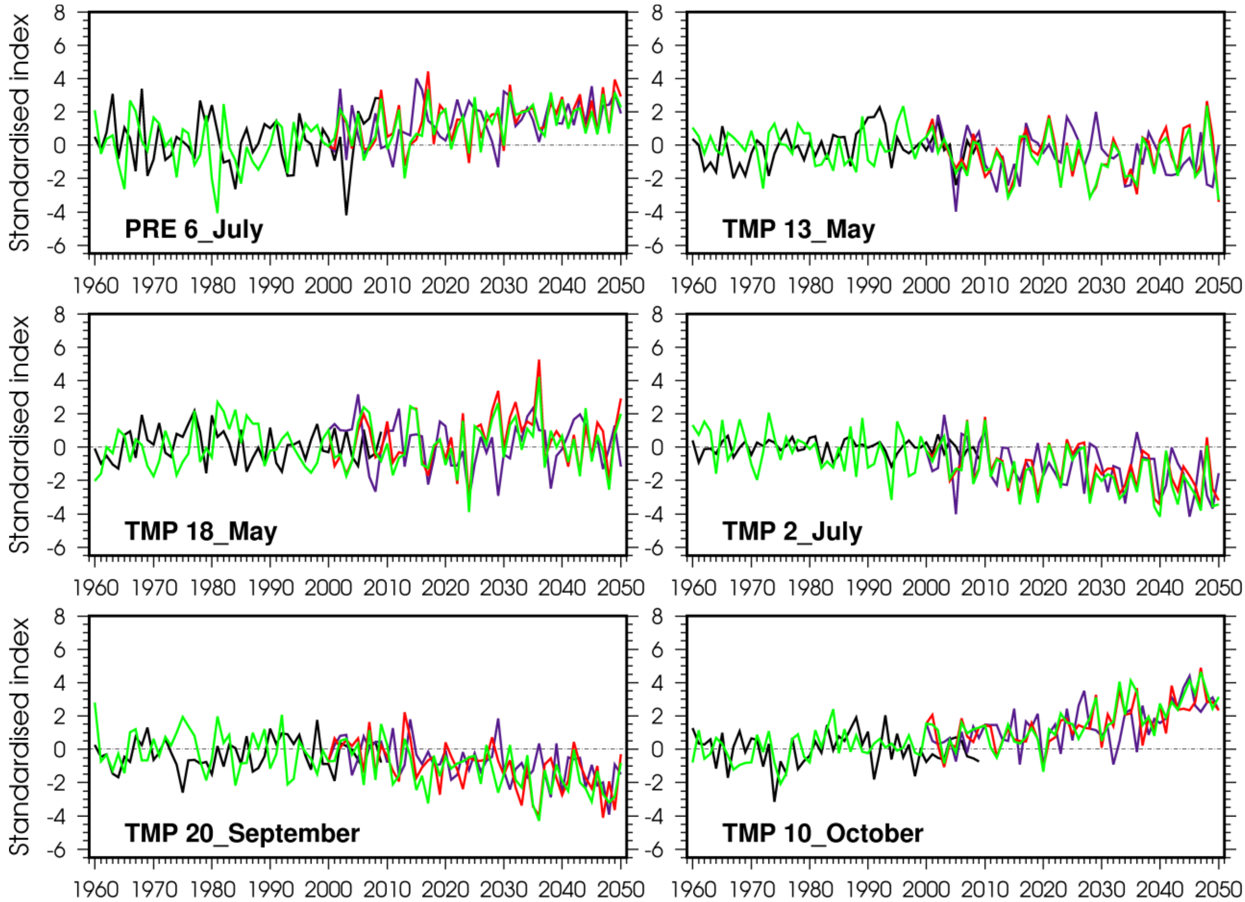
Appendix H: Temporal evolution of the current and future time series of the most important climatic factors for the prediction of sorghum production in Benin.



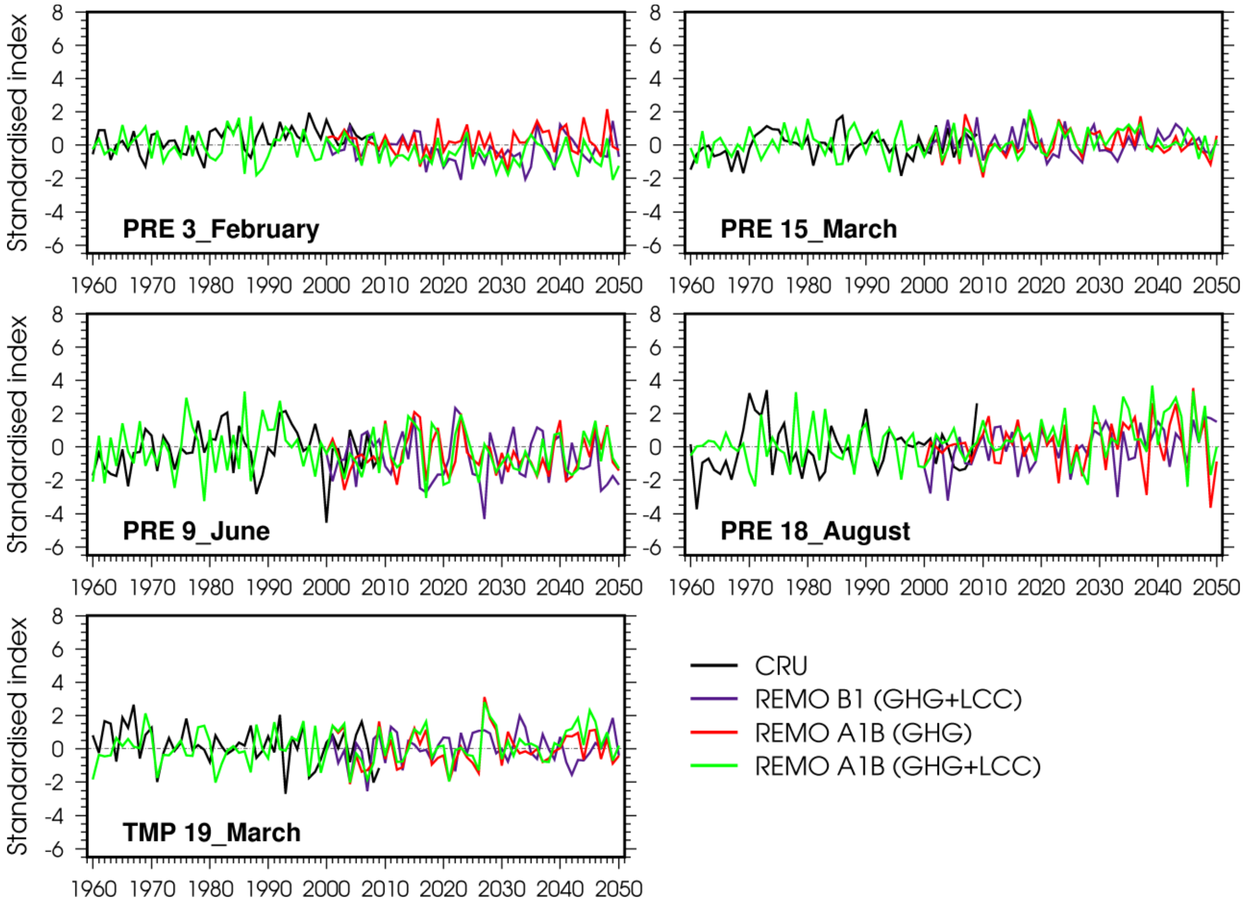
Appendix I: Temporal evolution of the current and future time series of the most important climatic factors for the prediction of groundnuts production in Benin.



Appendix J: Temporal evolution of the current and future time series of the most important climatic factors for the prediction of cotton production in Benin.



Appendix K: Temporal evolution of the current and future time series of the most important climatic factors for the prediction of yams production in Benin



Appendix L: Temporal evolution of the current and future time series of the most important climatic factors for the prediction of cassava production in Benin