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1. Introduction

This chapter describes the importance of agriculture in sub-Saharan Africa and the challenges the agricultural sector faces today and is likely to face in future. One of these challenges – climate change and its impacts on agriculture is defined as the core subject of this thesis and I later narrow this to the main objectives of this thesis and explain the methods applied to achieve them.

1.1. BACKGROUND

Agriculture in sub-Saharan Africa

Agricultural areas cover a large part of the Earth’s land area; for this reason, changes in agricultural systems cause important feedbacks to the atmosphere, soils, hydrological systems and more parts of the Earth system. For humans, agriculture is one of the most important land use activities, as it provides food, energy, fibre and other land-based products. Agriculture plays a key role in many countries, but in developing countries especially a sustainable agricultural sector ensures food and livelihood for many people and reduces poverty. In sub-Saharan Africa agriculture is also of major importance for humans which can be seen in the following indicators:

- Large parts of the land area are used as agricultural area. In 2010, 43 % (World: 38 %) of the land area was managed by humans as land under temporary and permanent crops, pasture and gardens, grazing land and land for agro-forestry (FAO, 2011). Approximately 8 % of the land area in tropical Africa is used for agricultural crops only (Ramankutty *et al.*, 2008) and Western Africa has the highest share of cropland in total land of 14 % (Fischer *et al.*, 2011). The most important agricultural areas lie in a band stretching from west to east between 5° N and 15° N and in a band running parallel to the Indian Ocean coastline from Ethiopia to South Africa (Figure 1-1).

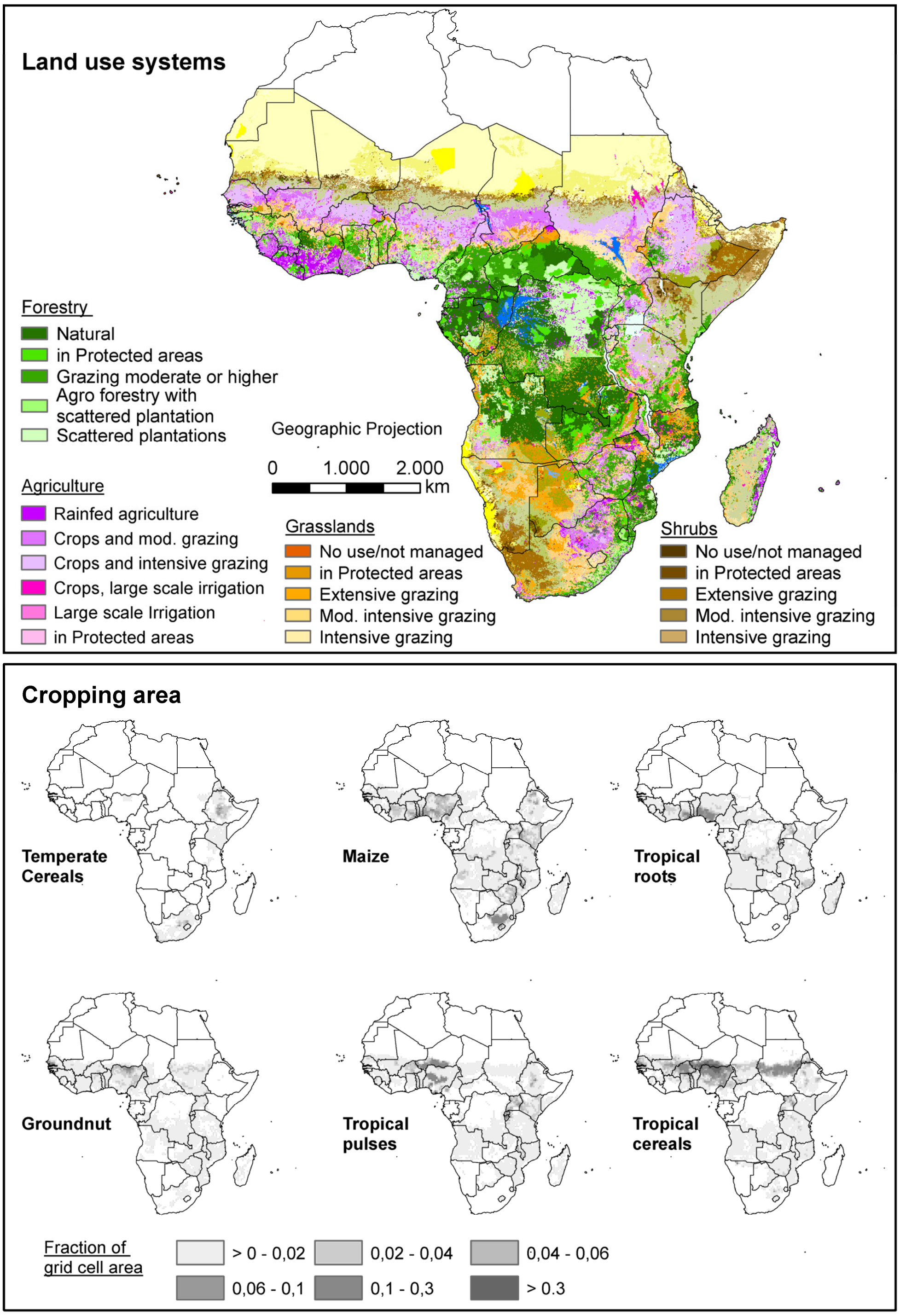

Figure 1-1 Land use systems and cropping area of six major food crops in sub-Saharan Africa. Top: Distribution of land use systems based on Nachtergaele & Petri (2008). Wetlands and open water bodies (blue colours), bare areas (yellow colours) and sparsely vegetated areas (olive colours) are not included in the legend. Bottom: Distribution of cropping areas are based on the land-use dataset from Fader *et al*. (2010).

- Economy depends on agriculture. 13 % (World 3 %) of the regions gross domestic product is produced by agriculture (World Bank, 2012), with many countries generating one third or more of their gross domestic product by agriculture (Central African Republic, Democratic Republic of Congo, Ethiopia, Ghana, Malawi, Mozambique, Rwanda, Sierra Leone). The majority of African countries is classified as “low-income food-deficit countries”, which indicates their low per capita gross national income and their dependency on food imports, making them vulnerable to food crises (FAO, 2008; FAO, 2012).

- People are reliant on the agricultural sector for their livelihood. 55 % (World 38 %) of the population depends on agriculture, hunting, fishing or forestry, including not only the economically active persons but also their non-working family members (FAO, 2011a).

However, agriculture in sub-Saharan Africa is rather unproductive compared to other world regions because of limited technical knowledge and finances which is required to increase production by the use of e.g. irrigation, fertilizer, machinery or soil-conservation measures, limited storage capacity for the produced agricultural goods and limited access to consumer markets (Godfray *et al.*, 2010). Almost two thirds of the cropping area is prepared by hand and the consumption of mineral fertilizer of 5 kg/ha in 1997-1999 is very low compared to East and South Asia with 194 kg/ha and 103 kg/ha respectively (FAO, 2003). Therefore, yields of the most important food crops in sub-Saharan Africa in the year 2000 only reached between 33 % (maize) and 88 % (cassava) of yields that would be achieved with global average management intensity (Dietrich *et al.*, 2012). Compared to the potentially achievable yield, the actually achieved crop yields are even lower by a factor of four (Fischer *et al.*, 2011). The unstable political and economical situation, security conflicts and unsecure land rights together with a high vulnerability to fluctuating world market prizes increase the pressure on the agricultural sector even more.

At the same time a doubling of the African population from 2000 to 2050 is expected (Figure 1-2), which together with shifting diets and incomes will cause large growth rates for the demand for food and livestock products of 2.8 % per year until 2030 and 2.0 % per year until 2050 thereafter (FAO, 2006). In the past, production of agricultural goods in sub-Saharan Africa was enhanced by expanding arable land, improving crop yields and increasing cropping intensity, i.e. expanding multiple cropping areas and reducing fallow periods. All three sources of growth contributed in equal parts and historical production growth between 1969-99 was 2.3 % per year (FAO, 2003). It is expected for 2030 that about 60 % of production growth will originate from increasing crop yields only (FAO, 2003). Large annual yield increases of 2.0 % per year until 2055 (World 1 % per year) are required to fulfill the demand for agricultural goods even in a business-as-usual scenario with increasing population, continued cropland expansion at historical rates and further globalization and trade liberalization. When taking increasing demand for bioenergy and extended efforts to protect intact and frontier forest into account as additional pressures, productivity is required to increase even more by 2.1 % p.a. and 2.3 % p.a., respectively (Lotze-Campen *et al.*, 2009).

In this context, climate change poses an additional risk for agriculture in sub-Saharan Africa. Warming during the 21st century is very likely to be larger than the global annual mean warming in Africa in all seasons and in all countries (Christensen *et al.*, 2007) making the continent one of the most susceptible world regions. Temperature is projected to increase by up to 3 °C until the end of the 21st century for the emission scenario A1b in equatorial and coastal areas and by up to 4 °C in the western Sahara compared to the end of the 20th century, and additionally a robust drying of the northern Sahara, the African west coast and Southern Africa is projected from most of the general circulation models (GCMs) (Christensen *et al.*, 2007) which will influence the growing conditions of agricultural crops.

Agricultural production in sub-Saharan Africa is expected to be severely influenced by climate change depending on the region, crop type, farming system, climate change scenario and method for assessing these effects. Mean country yields from eleven major food crops simulated with the dynamic global vegetation model LPJmL for five GCMs, three emission scenarios and two CO_2 fertilization scenarios are expected to change by -12.9 % to +17.3 % by 2050 (Figure 1-2). Food self-sufficiency will decrease most strongly in sub-Saharan Africa and the MENA region (Middle East and North Africa) compared to other world regions even if crop yields in some locations increase due to enhanced growing conditions. This unstable food situation increases the risk for regional food crises, and might also weaken the social and political stability of countries (Scheffran & Battaglini, 2011). A database on social conflicts in Africa lists over 7300 social conflict events between 1990 to 2010, including 324 demonstrations or violent riots because of food, water or subsistence issues (Hendrix & Salehyan, 2012).

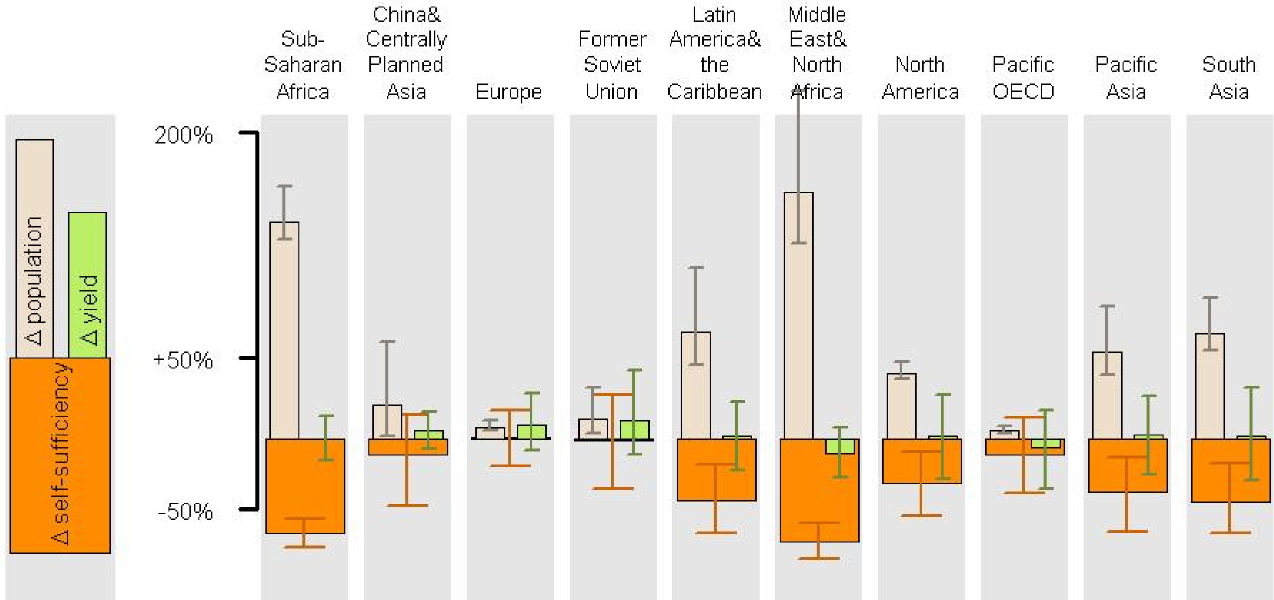

Figure 1-2 Mean change in crop yields, population and food self-sufficiency in ten world regions from 1996-2005 to 2046-2055 in 30 climate change scenarios (Müller *et al.*, 2009). Food self-sufficiency is calculated as the ratio of food production to food demand. Whiskers indicate the range of impacts. Population growth rates were taken from Nakicenovic & Swart (2000) for three emission scenarios.

Quantifying climate change impacts on agricultural vegetation

In the context of food supply and food security globally and in developing countries researchers aim at understanding and projecting climate change impacts on agricultural crops using various approaches. Among the first studies was the global food supply study from Rosenzweig & Parry (1994) which was later extended in the studies from Parry *et al.* (2004) and Parry *et al.* (2005). They use yield transfer functions derived from crop model simulations on the effects of climate change, increasing atmospheric CO_2 concentrations and adaptation options on crop yields. These results strongly depend on the crop model used to simulate crop responses to changing climate in a region. Rosenzweig & Parry (1994) extrapolated crop responses from 18 crop models and only 112 sites to national levels which are not representative for all regions, e.g. for Africa where crop model results for only one site in Zimbabwe was included. Another uncertainty in these studies arises from merging results from different crop models which differ in model parameters, model structure and settings. Each of them has to be calibrated to local soil, climate and agronomic conditions and cannot be extrapolated to other locations easily.

In the agro-ecological zones approach attainable crop yields are calculated depending on the growing season length, temperature, precipitation, soils and terrains (Fischer *et al.*, 2002b) with a simple crop model using empirical relationships without considering the underlying process (Tubiello & Ewert, 2002). Attainable yields will change if climatic conditions, and in turn the distribution of agro-ecological zones change, therefore the impact of slight climate change leading to a shift in zones might be overestimated considerably (Mendelson & Dinar, 1999). Also this approach projects the potential distribution of crops and crop yields rather than the actual situation and results need validation (Fischer *et al.*, 2002b).

A similar approach to the yield transfer functions is to develop a statistical model from historical crop yields and monthly temperature and precipitation data for the same period which was done for sub-Saharan Africa in Lobell *et al.* (2008) and in Schlenker & Lobell (2010). Here the crop response is not based on crop models but on crop yields measured in the field or estimated from farmers or agronomist which are also subject to various uncertainties (Fermont & Benson, 2011). Another deficiency arise from combining crop yield data with gridded climate data which might be of low quality in regions with only few weather stations. The most important limitation of statistical models is that they cannot be extrapolated to project crop yields in climatic conditions different from the historic climate (Lobell *et al.*, 2008). Lobell *et al.* (2008) therefore recommend applying statistical models only for studies until 2030 and rely on process-based crop models in studies for the end of the 21st century.

Process-based crop models simulate key plant processes like photosynthesis, plant phenology, carbon assimilation and allocation to plant organs and the dynamics of carbon and water from climate and soil data. They are therefore able to capture the dynamics of crop responses to climate change (Tubiello & Ewert, 2002). The study region stretches over 8000 km from north to south and over 7400 km from west to east so they need to be applicable at a large scale and for different environments. To my knowledge currently seven models designed to study the effect of climate change on agricultural vegetation on a large scale are published: DSSAT-CSM, ORCHIDEE-STICS, DayCent, LPJmL, GEPIC, ORCH-mil, and Pegasus (ordered ascending by the year of their first release). They differ in their model components and in the crops and management options included but all seven are intended to simulate crop growth, development and yield in a process-based way from soil and climate input data on a large scale. Table 1-1 shows the key reference describing each model, the crops included and the regions each model was applied for.

DSSAT-CSM, based on the decision support system DSSAT which was first released in 1989, is a combination of 16 individual crop and grass models from the CERES and CROPGRO model families. Researchers have frequently applied the DSSAT-CSM crop models in local studies on the effect of various management strategies on crop yields, and also in regional climate change impact studies (Jones *et al.*, 2003). DayCent, a daily time step model of the CENTURY biogeochemical model (Parton *et al.*, 1994), is an agro-ecosystem model which was adjusted at the Netherlands Environmental Assessment Agency to simulate the effects of climate, soil and crop management on crop yields of wheat, rice, maize and soybean at the global scale (Stehfest *et al.*, 2007).

Table 1-1 Large-scale crop models.

Model	Key reference	Scale / Regions	Crops
DSSAT-CSM	Jones *et al.* (2003)	Various single countries and world regions	chickpea, cowpea, dry bean, faba bean, maize, millet, peanut, potato, rice, sorghum, soybean, tomato, velvet bean, wheat
ORCHIDEE-STICS	Gervois *et al.* (2004)	Europe, USA	maize, soybean, winter wheat
DayCent	Stehfest *et al.* (2007)	Global	maize, rice, soybean, wheat
LPJmL	Bondeau *et al.* (2007)	Global	cassava, groundnut, maize, millet, pulses, rapeseed, rice, soybean, sugar beet, sunflower, wheat
GEPIC	Liu *et al.* (2007)	Global, China, sub-Saharan Africa	cassava, maize, millet, rice, sorghum, wheat
ORCH-mil	Berg *et al.* (2010)	West Africa	millet
Pegasus	Deryng *et al.* (2011)	Global	maize, soybean, wheat

GEPIC, which is a GIS based model of the EPIC model designed at the Swiss Federal Institute of Aquatic Science and Technology (Liu *et al.*, 2007), was applied for sub-Saharan Africa, China and on the global scale. The original EPIC model (Jones *et al.*, 1991; Williams *et al.*, 1989) provides a lot of important soil or crop parameters which are adopted from many other global crop models. Pegasus, recently developed at the Tyndall Centre for Climate Change Research and the McGill University, simulates maize, soybean and spring wheat growth, fertilizer application, irrigation and dynamic planting dates (Deryng *et al.*, 2011).

The ORCHIDEE-STICS and ORCH-mil models as well as the LPJmL model are based on the dynamic global vegetation models ORCHIDEE and LPJ-DGVM respectively which were further improved by including agricultural crops. ORCHIDEE-STICS was developed in 2004 at the Laboratoire des Sciences du Climat et de l'Environnement with the aim of including croplands (Gervois *et al.*, 2004). As the model was tested and validated only for winter wheat, maize and soybean but not for tropical crops, ORCH-mil was developed at the Institut Pierre Simon Laplace from the original ORCHIDEE model by including tropical C_4 crops. ORCH-mil is therefore able to simulate millet growth and yield in West Africa (Berg *et al.*, 2010).

LPJmL (Bondeau *et al.*, 2007) is an improved version of the LPJ-DGVM (Sitch *et al.*, 2003), developed at Lund in Sweden and Potsdam and Jena in Germany, as it now also includes agricultural crops. It is the most suitable tool for this study because of its ability to simulate crop yields for the major agricultural crops (Table 1-1) under current and future climates with a manageable amount of model parameters and low input requirements compared to e.g. DSSAT-CSM or GEPIC. The model's source code is written in C, which provides the possibility to include new functionalities. The model furthermore is already prepared to run on a high performance cluster computer, saving a lot of computation time. This allows obtaining simulation results for a large range of climate scenarios, emission scenarios, and model setups on a high spatial and temporal resolution.

LPJmL is able to simulate crop yields of eleven crop types in single-cropping systems; these are already validated for maize and wheat in temperate regions (Bondeau *et al.*, 2007; Fader *et al.*, 2010). A global land-use dataset and a method for representing agricultural management intensity was described recently in Fader *et al.* (2010), and evapotranspiration and crop water consumption were tested and validated against observational data (Gerten *et al.*, 2004; Rost *et al.*, 2008). The eleven crop types included in the model cover nearly 70 % of the area harvested and 48 % of the total crop production in sub-Saharan Africa. For studying climate change impacts in sub-Saharan Africa it was necessary to adapt the model to growing conditions in tropical ecosystems, which is done in this thesis for crop phenology and for cropping systems. Before, crops´ sowing dates were not represented well or even missing in the tropics. Therefore an improved rule for farmers´ planting decisions was developed in order to time sowing dates to the beginning of the rainy season. Furthermore, tropical cropping systems are much more complex than single cropping systems usually found in the temperate zone and therefore multiple cropping systems were implemented into LPJmL. For this purpose, the parameterization of a crop's growing period has to be changed to allow the simulation of short and long growing crop varieties depending on the length of the growing season and the cropping system. The model is further described in the "Materials and Methods" sections of each chapter highlighting the relevant model functionalities and model settings for each study.

Only few climate change impact studies with a focus on sub-Saharan Africa using a process-based crop model were conducted and described in the literature: for maize with CERES-maize (Jones & Thornton, 2003), for maize and beans with DSSAT (Thornton *et al.*, 2011), for six major crops with GEPIC (Liu *et al.*, 2008) and recently for maize with GEPIC (Folberth *et al.*, 2012). Additionally impact studies for individual countries or regions and crops can be found in literature for e.g. Cameroon with CropSyst (Laux *et al.*, 2010; Tingem & Rivington, 2009), East Africa with DSSAT (Thornton *et al.*, 2009; Thornton *et al.*, 2010), Mali with EPIC (Butt *et al.*, 2005), Nigeria with EPIC (Adejuwon, 2006), Ghana with GEMS (Tan *et al.*, 2010) and South Africa with CERES-maize (Walker & Schulze, 2008). However, all of the above-mentioned studies for sub-Saharan Africa and most of the regional studies omit including and discussing management strategies for adaptation and their effect on crop yield changes. The studies from Tingem & Rivington (2009), Laux *et al.* (2010) and Thornton *et al.* (2010) are an exception considering adapted sowing dates, adapted crop cultivars and shifts in farming systems but only for Cameroon and East Africa. The most comprehensive study from Butt *et al.* (2005) for Ghana simulates a wide range of biophysical adaptation, economic adaptation and policy based adaptation options like e.g. cropping patterns, the choice of improved and heat-resistant varieties and expansion of cropland. Theses studies are promising first regional assessments of the potentials of different adaptation options but lack in being widely applicable for the whole continent.

1.2. OBJECTIVES AND OUTLINE

This thesis is divided into three main parts; each of them intended to achieve specific goals but also following the findings from the preceding chapter in order to contribute answering the central research questions:

1. What are the impacts of climate change on agricultural crops in sub-Saharan Africa in the middle and end of the 21st century?

2. What is the potential of adaptation options for reducing negative climate change impacts in sub-Saharan Africa?

3. What are the determining factors for negative climate change impacts in sub-Saharan Africa?

Chapter 2: This first part sets the stage for quantifying climate change impacts on agricultural crops using a global crop model. It addresses the problem of simulating crop sowing dates on a global scale and of understanding the importance of climate in determining sowing dates. The global crop model so far is not able to simulate any sowing date for many important crops in the tropics and in other world regions they are incorrect or not validated to cropping calendars. This is a main shortcoming of the model as the timing of sowing largely determines crop growth and development, the occurrence of water stress in different development stages and final crop yields. Existing approaches either prescribe sowing dates (e.g. in GEPIC) or optimize them to reach highest possible crop yields (e.g. in DayCent). While the first approach cannot be applied in a climate change study as sowing dates will not be adapted to new climatic conditions, the optimization approach is limited by uncertainties in the model used to simulate crop yield. I develop an improved, simple rule for determining the timing of sowing from monthly climatology based on the existing approach described in Bondeau *et al.* (2007). Farmers in the tropics base their timing of sowing on the onset of the rainy season and this important management strategy needs to be considered in climate change impact studies as well. I also validate the simulated sowing dates from eleven crops by comparing them to sowing dates from a global crop calendar.

Chapter 3: From the results of chapter 2 I realized that substantial deviations in sowing dates occur in tropical regions and regions with high-land use intensity as only single cropping systems are considered in the model. Multiple cropping systems however are widely used in sub-Saharan Africa as farmers benefit from an increased number of harvests and from spreading the risk of crop failure across two or three growing periods. I consequently introduce simple multiple cropping systems into the model which is described in the second part. Multiple cropping systems are typically not considered in climate change impact studies because data on their distribution are not available or of low quality. The study from Thornton *et al.* (2009) is an exception making a first effort of considering a maize-bean system when quantifying the crop response to climate change in East Africa. I was able to identify the cropping system type and the relevant crop parameters for ten African countries based on an agricultural survey for more than 8600 households in sub-Saharan Africa. As the model is now well-prepared for a first application for tropical agricultural systems, I test the susceptibility of different cropping systems to climate change projected from three global circulation models. I compare different management strategies by varying the sowing date and the cropping system type. Both are potentially useful adaptation options for farmers in sub-Saharan Africa.

Chapter 4: In chapter 3 it is possible to identify key regions most susceptible to climate change and the potential of adaptation options. I then aim at understanding the determining factors for climate change impacts. Temperature and precipitation patterns are projected to change very differently in some regions and will therefore influence crops to a different extent. This study is motivated from the findings on separating the effects of temperature and precipitation in a statistical model (Schlenker & Lobell, 2010) and from the fact that studies in literature largely disagree about the most important climate variable determining future crop yields. I develop a method for studying temperature and precipitation effects on crop yields separately and in combination in order to contribute solving this scientific problem. I aim at identifying the limiting effect for maize as an exemplarily crop which will help to prioritize future research needs in drought and heat stress breeding programmes and to identify adequate crop varieties and adaptation options in different environments.

Figure 1-3 shows on overview of the outline.

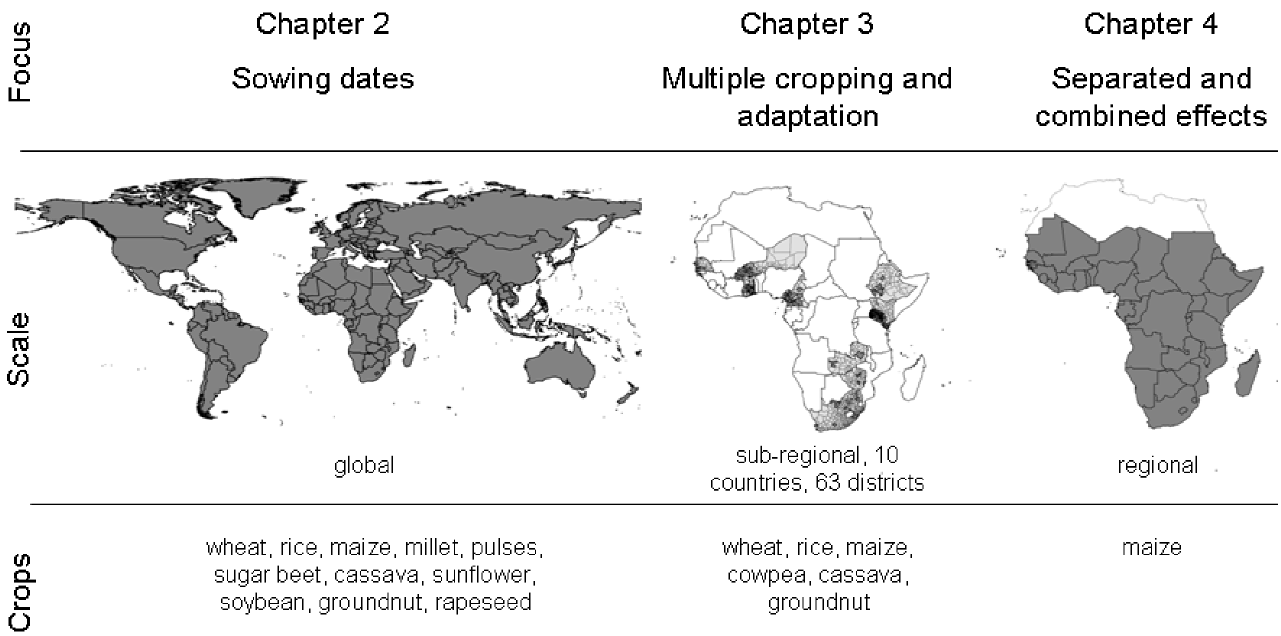

Figure 1-3 Graphical abstract of thematic focus, scale of study region and crops studied in the main chapters.

2. Climate-driven simulation of global crop sowing dates

The aim is to simulate sowing dates of eleven major annual crops at global scale at high spatial resolution, based on climatic conditions and crop-specific temperature requirements. Sowing dates under rainfed conditions are simulated deterministically based on a set of rules depending on crop- and climate-specific characteristics. We assume that farmers base their timing of sowing on experiences with past precipitation and temperature conditions, with the intra-annual variability being especially important. The start of the growing period is assumed to be dependent either on the onset of the wet season or on the exceeding of a crop-specific temperature threshold for emergence. To validate our methodology, a global data set of observed monthly growing periods (MIRCA2000) is used.

We show simulated sowing dates for eleven major field crops worldwide and give rules for determining their sowing dates in a specific climatic region. For all simulated crops, except for rapeseed and cassava, in at least 50 % of the grid cells and on at least 60 % of the cultivated area, the difference between simulated and observed sowing dates is less than 1 month. Deviations of more than 5 months occur in regions characterized by multiple cropping systems, in tropical regions which, despite seasonality, have favourable conditions throughout the year, and in countries with large climatic gradients.

We conclude that sowing dates under rainfed conditions for various annual crops can be satisfactorily estimated from climatic conditions for large parts of the Earth. Our methodology is globally applicable and therefore suitable for simulating sowing dates as input for crop growth models applied at global scale and taking climate change into account.

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2.1. INTRODUCTION

In addition to soil characteristics, the suitability of a region for agricultural production is largely determined by climate. Precipitation controls water availability in rainfed and to some extent in irrigated production systems, temperature controls the length and timing of the various phenological stages on one hand and the productivity of crops on the other hand (Larcher, 1995; Porter & Semenov, 2005), and available radiation controls, via energy supply, the photosynthetic rate (Larcher, 1995). Furthermore, low temperatures and inadequate soil water availability during germination lead to low emergence rates and poor stand establishment, due to seed and seedling diseases, as shown e.g. in sugar beet (Jaggard & Qi, 2006) and soybean (Tanner & Hume, 1978), leading to low yield levels. To maximize or optimize production, farmers therefore aim at selecting suitable cropping periods, crops, and management strategies.

With climate change, climatic conditions during the growing period will change (Burke *et al.*, 2009). Both mean and extreme temperatures are expected to increase for large parts of the Earth with rising CO_2 concentrations (Yonetani & Gordon, 2001). To cope with these changing climatic conditions, adaptation strategies are required, e.g. changing the timing of sowing (Rosenzweig & Parry, 1994; Tubiello *et al.*, 2000).

Crop growth models are suitable tools for the quantitative assessment of future global crop productivity. They are increasingly applied at global scale (e.g. Bondeau *et al.* (2007), Liu *et al.* (2007), Parry *et al.* (2004), Stehfest *et al.* (2007), and Tao *et al.* (2009)). Key inputs for crop growth models are weather data and information on management strategies, e.g. the choice of crop types, varieties and sowing dates. Future weather data for global application of crop growth models are usually provided by global circulation models (GCMs). It can be assumed that farmers will adapt sowing dates to changes in climatic conditions and therefore current sowing date patterns (Portmann *et al.*, 2008; Sacks *et al.*, 2010) will change over time. To adequately simulate sowing dates for future climatic conditions, it is necessary to understand the role of climate in the determination of sowing dates.

Different approaches are applied in existing crop models to determine current and future sowing dates. Crop models, such as LPJmL (Bondeau *et al.*, 2007), identify sowing dates from climate data and crop water and temperature requirements for sowing. Another approach is to optimize sowing dates using the crop model by selecting the date which leads to the highest crop yield, a method applied e.g. in DayCent (Stehfest *et al.*, 2007) or by selecting the optimal growing period based on predefined crop-specific requirements, as e.g. in GAEZ (Fischer *et al.*, 2002b). Finally, pre-defined sowing dates based on observations have been used, e.g. in the Global Crop Water Model (GCWM) (Siebert & Döll, 2008) and in GEPIC (Liu *et al.*, 2007).

In contrast to pre-defined sowing dates, determining sowing dates from climate data, as well as the optimization of sowing dates, provides the opportunity to simulate changing sowing dates under future climatic conditions. However, outcomes of the optimization method are largely dependent on the crop model used, adding extra uncertainties to the outcomes. The calculation procedure currently applied in LPJmL (Bondeau *et al.*, 2007) is not applicable for all crops in different climatic regions and has only been evaluated for temperate cereals. Therefore, our aims are to: (1) describe an improved method to identify sowing dates within a suitable cropping window, based on climate data and crop-specific requirements at global scale and (2) evaluate the agreement with global observations of sowing dates. Non-climatic reasons for the timing of sowing like e.g. the demand for a particular agricultural product during a certain period or the availability of labour and fertilizer are not considered in the simulations of sowing dates. The outcomes of our analysis will be: (1) a set of rules to determine the start of the growing period for major crops in different climates, (2) an evaluation of the importance of climate in determining sowing dates, and (3) maps of simulated global patterns of sowing dates. Our outcomes will lead to improved simulation of crop phenology at the global scale, which will make an important contribution to estimates of carbon and water fluxes in dynamic global vegetation models. Furthermore, sowing dates in suitable cropping windows under future climatic conditions can be estimated, and are likely to improve integrated assessments of global crop productivity under climate change.

2.2. MATERIALS AND METHODS

Input climate data

Monthly data of temperature, precipitation, and number of wet days on a 0.5° by 0.5° resolution are based on a data set compiled by the Climatic Research Unit (Mitchell & Jones, 2005). A weather generator distributes monthly precipitation to observed number of wet days, which are distributed over the month taking into account the transition probabilities between wet and dry phases (Geng *et al.*, 1986). Daily mean temperatures are obtained by linear interpolation between monthly mean temperatures.

Deterministic simulation of sowing dates

Sowing dates, averaged over the period from 1998 to 2002, were simulated deterministically, based on a set of rules depending on crop and climate characteristics. Sowing dates were simulated for eleven major field crops (wheat, rice, maize, millet, pulses, sugar beet, cassava, sunflower, soybean, groundnut, and rapeseed) under rainfed conditions. We did not consider irrigated systems, because if irrigation is applied, sowing dates are strongly determined by the availability of irrigation water (e.g. melting glaciers upstream) and labor, factors not considered in the methodology.

We assumed that farmers base the timing of their sowing on experiences with past weather conditions: e.g. in southern India, farmers use a planting window for rainfed groundnut based on experiences of about 20 years (Gadgil *et al.*, 2002), in the African Sahel, knowledge for decision making is influenced by previous generations' observations (Nyong *et al.*, 2007), while farmers in the south-eastern USA are expected to adapt their management to changes in climatic conditions within 10 years (Easterling *et al.*, 2003). In order to be able to use a generic rule across the Earth, we represented the experiences by farmers with past weather conditions by exponential weighted moving average climatology. This gave a higher importance to the monthly climate data from the most recent years than the monthly climate data from less recent years, for the calculation of the average monthly climate data. Consequently, the month of sowing is determined by past climatic conditions, whereas the actual sowing date within that month is simulated based on the daily temperature and precipitation conditions from the specific year. Figure 2-1 shows a schematic overview of the methodology followed.

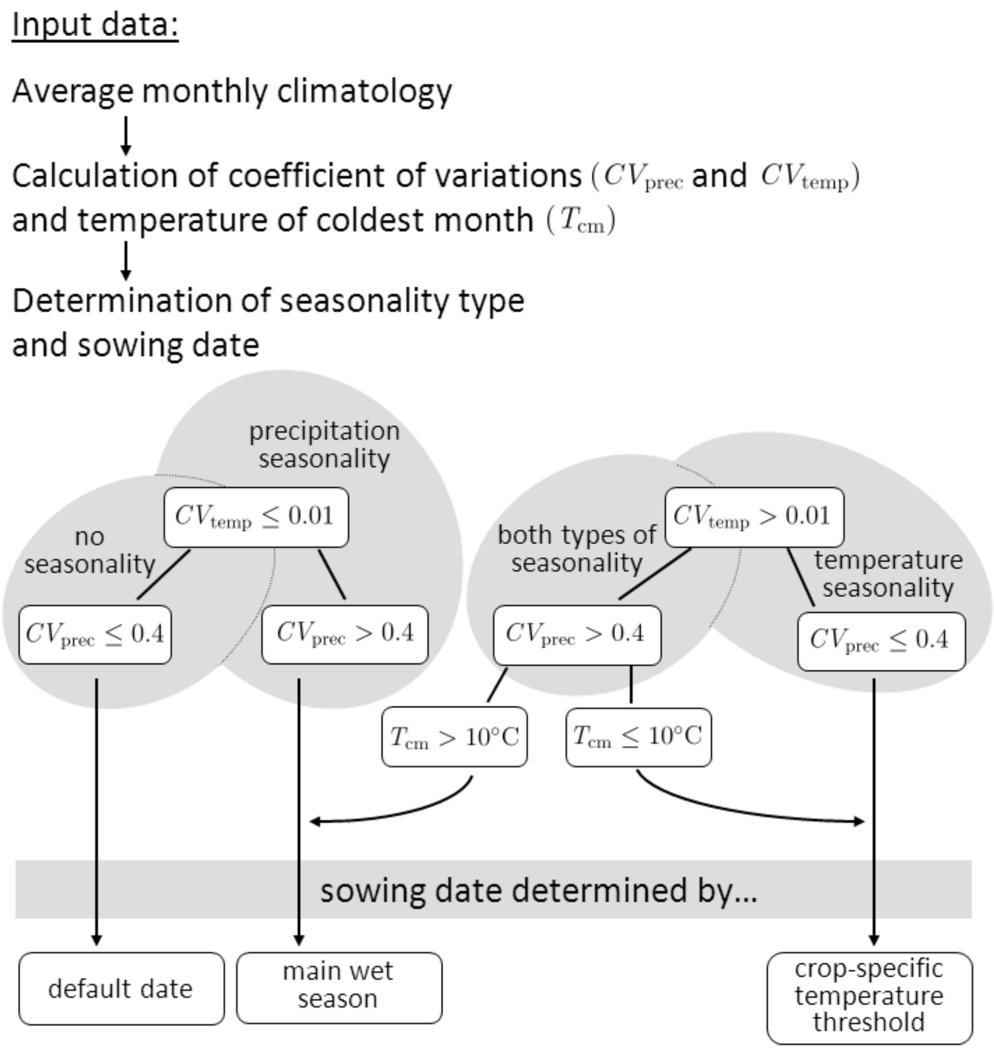

Figure 2-1 Procedure to determine seasonality type and sowing date.

Determination of seasonality types

We assumed that the timing of sowing is dependent on precipitation and temperature conditions, with the intra-annual variability of precipitation and temperature being especially important. Precipitation and temperature seasonality of each location are characterized by the annual variation coefficients for precipitation (CV_{prec}) and temperature (CV_{temp}), calculated from past monthly climate data. To prevent interference from negative temperatures if expressed in degrees Celsius, temperatures are converted to the Kelvin scale. The variation coefficients are calculated as the ratio of the standard deviation to the mean:

$$CV_j = \frac{\sigma_j}{\mu_j}$$

with $\sigma_j = \sqrt{\frac{1}{12-1} \times \sum_{m=1}^{12} (\overline{X}_{m,j} - \mu_j)^2}$, $\mu_j = \frac{1}{12} \times \sum_{m=1}^{12} \overline{X}_{m,j}$, and,

$\overline{X}_{m,j} = \alpha \times X_{m,j} + (1 - \alpha) \times \overline{X}_{m,j\text{-}1}$,

where $X_{m,j}$ is the mean temperature (K) or precipitation (mm) of month *m* in year *j*, $\overline{X}_{m,j}$ the exponential weighted moving average temperature or precipitation of month *m* in year *j*, μ the annual mean temperature or precipitation in year *j,* σ the standard deviation of temperature or precipitation in year *j*, and α the coefficient, representing the degree of weighting decrease (with a value of 0.05). The calculation was initialised by $\overline{X}_{m,j=1} = X_{m,j=1}$.

Variation coefficients are commonly used to distinguish different seasonality type (Hulme, 1992; Jackson, 1989; Walsh & Lawler, 1981). Walsh & Lawler (1981) provided a classification scheme for characterising the precipitation pattern of a certain region based on the value of CV_{prec} and suggested describing a region with a CV_{prec} exceeding 0.4 as “rather seasonal” or “seasonal”. We could not find such a value for CV_{temp} in the literature: however, in order to simulate a reasonable global distribution of temperate and tropical regions, we assumed temperature seasonality if CV_{temp} exceeds 0.01. Accordingly, four seasonality types can be distinguished:

1. no temperature and no precipitation seasonality
2. precipitation seasonality
3. temperature seasonality
4. temperature and precipitation seasonality

In situations with a combined temperature and precipitation seasonality, we additionally considered the mean temperature of the coldest month. If the mean temperature of the coldest month exceeded 10°C, we assumed absence of a cold season, i.e. the risk of occurrence of frost is negligible, which is in line with the definition of Fischer *et al.* (2002b). Consequently, temperatures are high enough to sow year-round, therefore, precipitation seasonality is determining the timing of sowing. If the mean temperature of the coldest month is equal to or below 10°C, we assumed temperature seasonality to be determining the timing of sowing.

Determination of the start of the growing period

The growing period is the period between sowing and harvesting of a crop. We applied specific rules per seasonality type to simulate sowing dates (Figure 2-1). In regions with no seasonality in precipitation and temperature conditions, crops can be sown at any moment and we assigned a default date as sowing date (1 January, for technical reasons).

In regions with precipitation seasonality, we assumed that farmers sow at the onset of the main wet season. The precipitation-to-potential-evapotranspiration ratio is used to characterize the wetness of months, as suggested by Thornthwaite (1948). Potential evaporation is calculated using the Priestley-Taylor equations (Priestley & Taylor, 1972), with a value of 1.391 for the Priestley-Taylor coefficient (Gerten *et al.*, 2004). As a region may experience two or more wet seasons, the main wet season is identified by the largest sum of monthly precipitation-to-potential-evapotranspiration ratios of 4 consecutive months; 4 months were selected because the length of that period captures the length of the growing period of the majority of the simulated crops. Crops are sown at the first wet day in the main wet season of the simulation year i.e. with a daily precipitation higher than 0.1mm, which is in line with the definition of New *et al.* (1999).

In regions with temperature seasonality, the onset of the growing period depends on temperature. Crop emergence is related to temperature, accordingly, sowing starts when daily average temperatures exceed a certain threshold (Larcher, 1995). Crop varieties such as winter wheat and winter rapeseed require vernalizing temperatures and are therefore sown in autumn. Accordingly, for those crops, temperatures should fall below a crop-specific temperature threshold (Table 2-1). To be certain to fulfil vernalization requirements, crop-specific temperature thresholds are set around optimum vernalization temperatures, which resembles the practice applied by farmers in e.g. southern Europe (Harrison *et al.*, 2000). Earlier research, i.e. the analysis of Sacks *et al.* (2010) on crop planting dates, showed that temperatures at which sowing usually begins vary among crops, but are rather uniform or in the same range for a given crop throughout large regions. For simplicity, we assumed that one crop-specific temperature threshold is applicable globally. The sowing month is the month in which mean monthly temperatures of the past ($\overline{X}_{m,j}$) exceed (or fall below) the temperature threshold. In addition, typical daily temperatures of the preceding month are checked. If the typical daily temperature of the last day of this preceding month already exceed (or fall below) the temperature threshold, this month is selected as the sowing month. Typical daily temperatures are computed by linearly interpolating the mean monthly temperatures of the past ($\overline{X}_{m,j}$). Next, daily average temperature data of the simulated year determine the specific date of sowing in the sowing month, in order to consider the climatic specificity of the simulated year.

We derived the temperature thresholds, only for non-vernalizing crops, by decreasing and increasing the temperature thresholds given by Bondeau *et al.* (2007) for sowing, by -4°C to +8°C and selected the temperature thresholds that resulted in an optimal agreement between observed and simulated sowing dates in regions with temperature seasonality. The resulting temperature thresholds for sowing are plausible when compared to base temperatures for emergence found in the literature (Table 2-1). Although our temperature thresholds are slightly higher or at the top end of the found range of base temperatures, temperatures just above these base temperatures for emergence will result in retarded emergence (Jaggard & Qi, 2006).

Table 2-1 Crop-specific temperature thresholds for sowing.

Crop	**Base temperature for emergence found in literature**			**Temperature used in this study (°C)**
	Reference and temperature (°C)		Range (°C)	
Cassava	(Hillocks & Thresh, 2002) (Keating & Evenson, 1979)	16 12 − 17	12 − 17	22
Groundnut	(Angus *et al.*, 1980) (Mohamed *et al.*, 1988) (Prasad *et al.*, 2006)	13.3 8 − 11.5 11 − 13	8 − 13.3	15
Maize	(Birch *et al.*, 1998) (Coffman, 1923) (Grubben & Partohardjono, 1996) (Kiniry *et al.*, 1995) (Pan *et al.*, 1999) (Warrington & Kanemasu, 1983)	8 10 10 12.8 10 9	8 − 12.8	14
Millet	(Garcia-Huidobro *et al.*, 1982) (Grubben & Partohardjono, 1996) (Kamkar *et al.*, 2006) (Mohamed *et al.*, 1988)	10 − 12 12 7.7 − 9.9 8 − 13.5	7.7 − 13.5	12
Pulses	(Angus *et al.*, 1980) − field pea (Angus *et al.*, 1980) − cowpea (Angus *et al.*, 1980) − mungbean	1.4 11 10.8	1.4 − 11	10
Rice	(Rehm & Espig, 1991) (Yoshida, 1977)	10 16 − 19	10 − 19	18
Soybean	(Angus *et al.*, 1980) (Tanner & Hume, 1978) (Whigham & Minor, 1978)	9.9 10 5	5 − 10	13
Spring rapeseed	(Angus *et al.*, 1980) (Booth & Gunstone, 2004) (Vigil *et al.*, 1997)	2.6 2 1	1 − 2.6	5
Spring wheat	(Addae & Pearson, 1992) (Del Pozo *et al.*, 1987) (Khah *et al.*, 1986) (Kiniry *et al.*, 1995)	0.4 2 1.9 2.8	0.4 − 2.8	5
Sugar beet	(Jaggard & Qi, 2006) (Rehm & Espig, 1991)	3 4	3 − 4	8
Sunflower	(Angus *et al.*, 1980) (Khalifa *et al.*, 2000)	7.9 3.3 − 6.7	3.3 − 7.9	13
Winter rapeseed*				< 17
Winter wheat*				<12

* Winter wheat and winter rapeseed are sown in autumn, as both crops have to be exposed to vernalizing temperatures. Their base temperatures for emergence have been selected around the optimum vernalization temperatures.

Procedure of validating the methodology

Data set of observed growing periods: MIRCA2000

To validate our methodology, the global data set of observed growing areas and growing periods, MIRCA2000 (Portmann *et al.*, 2008) at a spatial resolution of 0.5° by 0.5° and a temporal resolution of a month was used. Monthly data in MIRCA2000 were converted to daily data following the approach of Portmann *et al.* (2010), by assuming that the growing period starts at the first day of the month reported in MIRCA2000. The data set includes twenty-six annual and perennial crops and covers the time period between 1998 and 2002. For most countries, MIRCA2000 was derived from national statistics. For China, India, USA, Brazil, Argentina, Indonesia and Australia, sub-national information was used as well, mainly from the Global Information and Early Warning System on food and agriculture (FAO-GIEWS) and from the United States Department of Agriculture (USDA). Based on the extent of cropland, derived from satellite-based remote sensing information and national statistics (Ramankutty *et al.*, 2008), the growing area combined with the growing period of each crop was distributed to grid cells at a spatial resolution of 5' by 5', which were finally aggregated to grid cells of 0.5° by 0.5° (Portmann *et al.*, 2008). Sacks *et al.* (2010) recently compiled a similar data set of crop planting dates, also using cropping calendars from FAO-GIEWS and USDA. MIRCA2000, in contrast, distinguishes between rainfed and irrigated crops, which allows a comparison of sowing dates for rainfed crops only.

MIRCA2000 distinguishes up to five possible growing periods per grid cell, reflecting different varieties of wheat, rice and cassava and/or multiple-cropping systems of maize and rice, but for most crops only one growing period per year is reported. For wheat, spring varieties and winter varieties are distinguished; for rice a number of growing periods are distinguished, i.e. for upland rice, deepwater rice, and paddy rice, with up to three growing periods for paddy rice (Portmann *et al.*, 2010). For cassava, an early and a late ripening variety with different sowing dates are distinguished.

In contrast, we assumed only one growing period per year in single cropping systems. For wheat and rapeseed, we distinguished between spring and winter varieties: in regions with suitable climatic conditions for both varieties, the winter variety has been selected. If daily average temperatures exceed 12°C (17°C for rapeseed) year-round or drop below that threshold before 15 September (northern hemisphere) or before 31 March (southern hemisphere), the spring variety has been selected. As MIRCA2000 reports several growing periods for some crops, it was difficult to select the most suitable growing period for comparison. Consequently, we selected the best corresponding growing period, indicating the reasonability of the simulated sowing dates, but not their representativeness. Portmann *et al.* (2010) reported several uncertainties and limitations of MIRCA2000: data gaps and uncertainties in the underlying national census data, the lack of sub-national data for some larger countries and therefore neglect of possible effects on growing periods due to climatic gradients, and the fact that very complex cultivation systems, in which more than one crop is grown on the same field at the same time, could not be represented adequately. These constraints, as well as the temporal resolution of one month of MIRCA2000 should be taken into account in assessing the comparison between observed and simulated sowing dates.

Methodology for comparing observed and simulated sowing dates

To assess the degree of agreement between simulated and observed sowing dates, two indices of agreement were calculated for each crop: the mean absolute error (ME) and the Willmott coefficient of agreement (W) (Willmott, 1982):

$$ME = \frac{\sum_{i=1}^{N} |S_i - O_i| \times A_i}{\sum_{i=1}^{N} A_i} \qquad W = 1 - \frac{\sum_{i=1}^{N} (S_i - O_i)^2 \times A_i}{\sum_{i=1}^{N} (|S_i - \overline{O}| + |O_i - \overline{O}|)^2 \times A_i}$$

where, S_i is the simulated and O_i the observed sowing date (day of year) in grid cell *i*, $\overline{O}$ the mean observed sowing date (day of year), A_i the cultivated area (ha) of the crop in grid cell *i*, and *N* the number of grid cells.

Indices are area-weighted, so the agreement in the main growing areas of a crop is considered more important than the agreement in areas where the crop is grown on smaller areas. W is dimensionless, ranging from 0 to 1, with 1 showing perfect agreement. ME indicates the global average error between simulations and observations, W additionally considers the spatial patterns in observations and systematic differences between simulations and observations (Willmott, 1982). In addition to the two indices of agreement, we calculated the cumulative frequency distribution of the mean absolute error in days between the observed and simulated sowing dates, to show the frequency of grid cells and of cultivated area below a certain threshold.

2.3. RESULTS

We show the global distribution of seasonality types as well as sowing dates simulated with the presented methodology and the comparison with observed sowing dates from MIRCA2000. To assess these results, we performed a sensitivity analysis of crop yields on sowing dates (see Appendix B). Regions without seasonality are not considered in the evaluation of results, because sowing dates do not substantially affect crop yield there, as indicated by the sensitivity analysis (Figure B-1 in Appendix B).

Seasonality types

The spatial pattern of the calculated seasonality types (Figure 2-2) resembles the distribution of various climates across the Earth. Locations around the equator in the humid tropics are characterized by a lack of seasonality in both temperature and precipitation (e.g. Iquitos, Peru). The semi-humid tropics, with dry and wet seasons, are characterized by precipitation seasonality only (e.g. Abuja, Nigeria). The temperate zones in the humid middle latitudes with warm summers and cool winters are characterized by temperature seasonality (e.g. Amsterdam, the Netherlands). In locations with precipitation seasonality and a distinct cold season (e.g. Kansas City, USA), low temperatures limit the growing period of crops and sowing dates are simulated based on temperature. If a cold season is absent in a location with precipitation seasonality (e.g. Delhi, India), sowing dates are simulated based on precipitation. Figure 2-3 shows annual variations in temperature and precipitation for five locations and Figure 2-2 indicates their location.

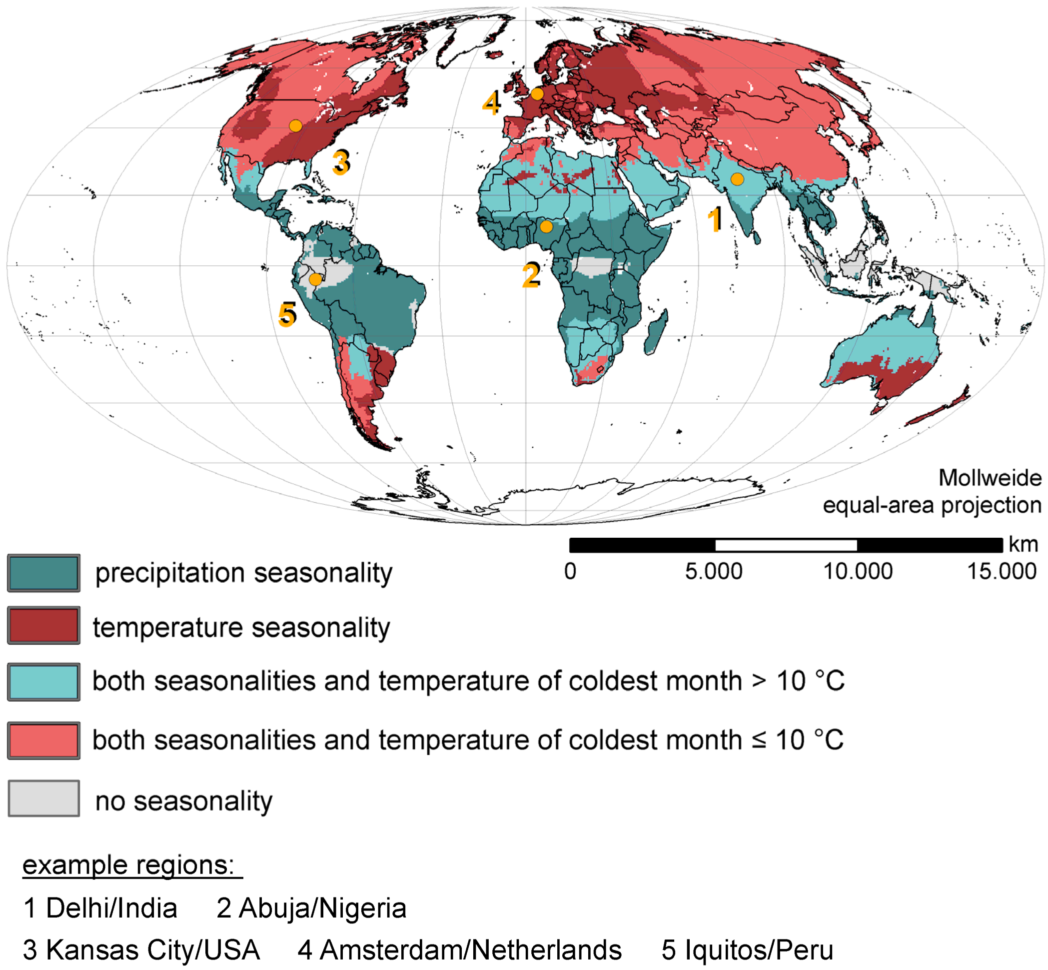

Figure 2-2 Global distribution of seasonality types. Seasonality types are based on the annual patterns of precipitation and temperature. For each seasonality type one example region is marked.

Comparison of observed and simulated sowing dates

Figure A-1 to Figure A-11 in Appendix A show simulated and observed sowing dates, as well as the deviations per crop. As a condensed overview, Figure 2-4 shows the cumulative frequency distribution of the mean absolute error between observations and simulations for all crops, for all grid cells combined, and separately for the two rules.

Figure 2-4 and the difference maps (Figure A-1a to Figure A-11a) indicate close per grid cell agreement for rice, millet, sugar beet, sunflower, soybean and groundnut globally, as well as close agreement for pulses in regions where temperature seasonality determines sowing dates. Figure 2-4 shows that for all crops except rapeseed and cassava, in at least 50% of the grid cells and on at least 60% of the cultivated area, the error between simulations and observations is less than 1 month. Even in regions where simulated sowing dates deviate from observed sowing dates by 1 month, the results from the sensitivity analysis suggest that this range hardly affects computed crop yields from a global dynamic vegetation and crop model (Figure B-1), if they fall within a suitable growing period (e.g. the main wet season or spring season).

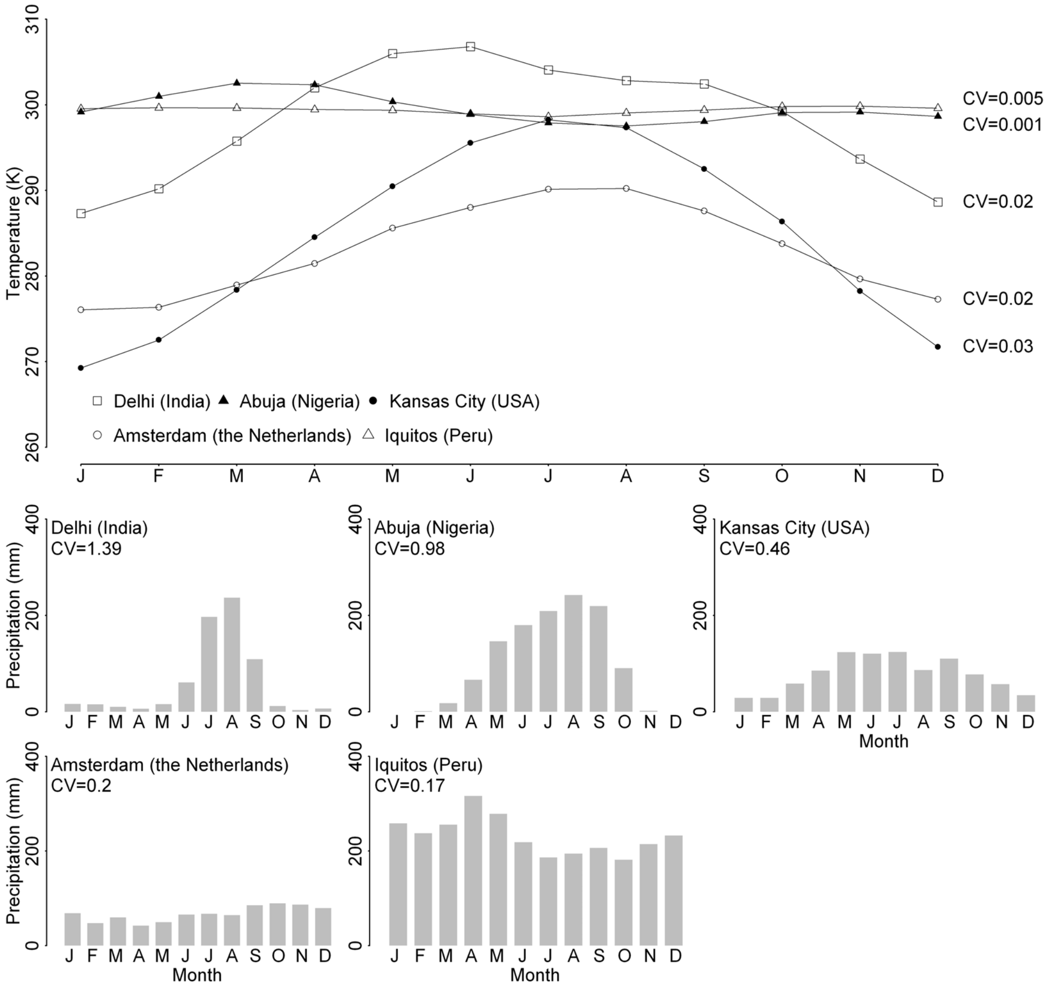

Figure 2-3 Annual variations in temperature (above) and precipitation (below) for five locations.

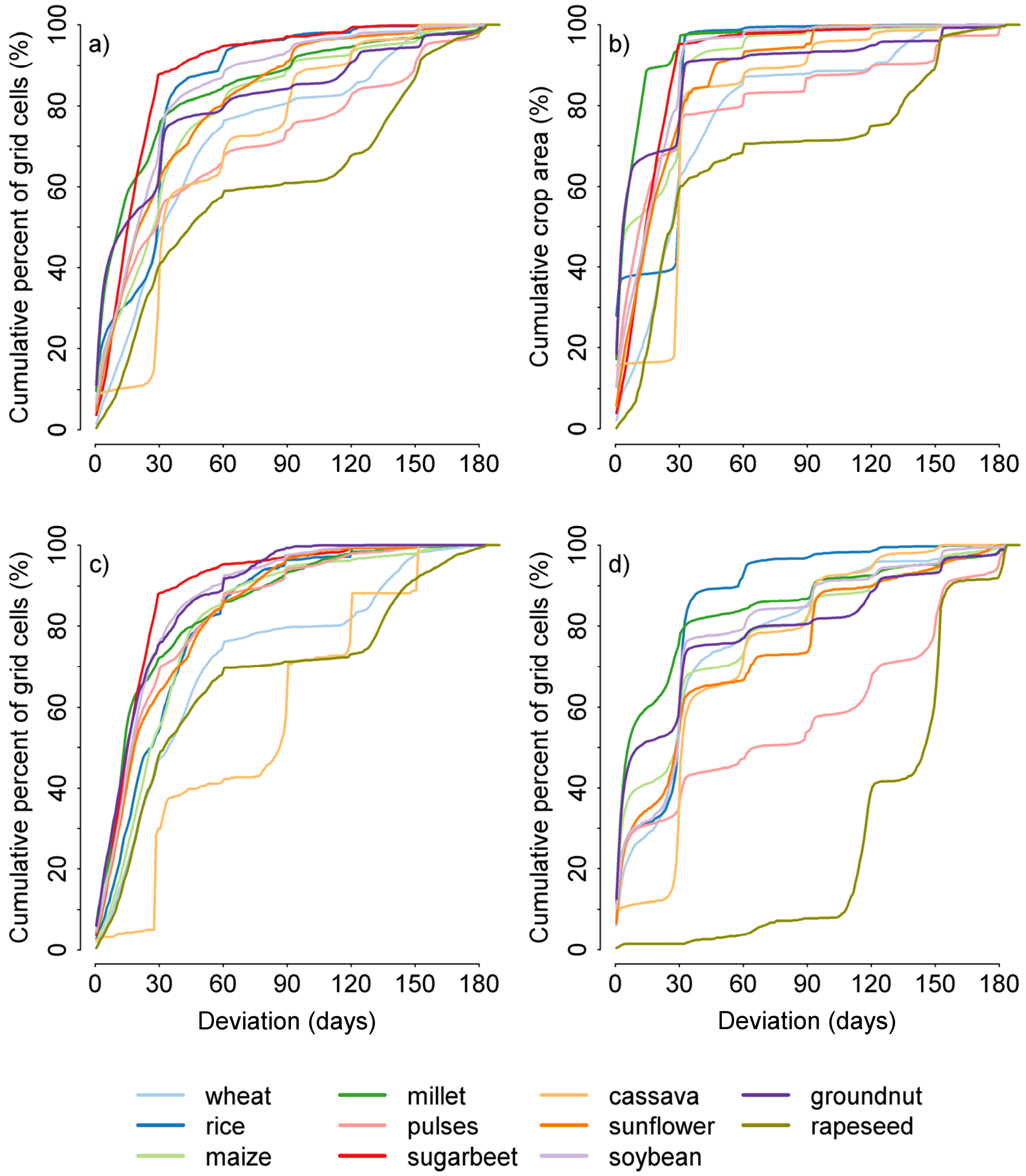

Figure 2-4 Cumulative percent of grid cells (or crop area in a grid cell) with certain differences between observed and simulated sowing date. Deviations are shown for: a) all grid cells, b) crop area of all grid cells, c) grid cells where sowing dates are determined by a temperature threshold, and d) grid cells where sowing dates are determined by the onset of the main wet season. Grid cells with a crop area smaller than 0.001% of the grid cell area are not considered in the calculations. Curves are only shown if the number of grid cells in which a specific rule to determine the sowing date for a specific crop is applied exceeds 1% of all grid cells.

Poor agreement, with differences between simulations and observations of more than 5 months, is found: for wheat in Russia; for maize and cassava in Southeast Asia and China (and in East Africa for maize); for pulses in Southeast Asia, India, West and

East Africa, the Southeast region of Brazil and southern Australia; for groundnut in India and Indonesia, for rapeseed in northern India, southern Australia and southern Europe. Deviations are also large for crops growing in the southern part of the DR Congo, in Indo-China and in regions around the equator.

Table 2-2 shows both, the mean absolute error (ME) and the Willmott coefficient of agreement (W) for each crop for all cells where the crop is grown and differentiated for the rules to determine sowing date. The mean absolute error (ME) for all cells is less than 2 months, with the exception of pulses. For wheat (without Russia), rice, millet, sugar beet and sunflower, the agreement is even closer, with a difference of at most one month between simulations and observations. The Willmott coefficients (W) are high, and show close agreement between simulations and observations (W > 0.8) with the exception of pulses. Both indices show closer agreement for pulses, groundnut, sunflower and rapeseed in regions where sowing dates are determined by the temperature threshold than in regions where the onset of the main wet season determines sowing date. In contrast, both indices show closest agreement for millet in regions where sowing dates are determined by the onset of the wet season.

Table 2-2 Indices of agreement between simulated sowing dates and observed sowing dates.

	Mean absolute error (days)			**Willmott coefficient (dimensionless)**				
	all cells	Sowing date determined by:		all cells	Sowing date determined by:		% of all cells	
		main wet season	temp. threshold		main wet season	temp. threshold	main wet season	temp. threshold
Wheat	44 (30*)	37 (37*)	45 (**30***)	0,88 (0,96*)	0,9 (0,9*)	0,88 (**0,96***)	18 (22*)	82 (78*)
Rice	24	**22**	23	0,92	0,92	**0,94**	82	18
Maize	34	38	**32**	0,89	**0,89**	0,87	48	52
Millet	15	**14**	33	0,91	**0,95**	0,86	63	37
Pulses	69	79	**37**	0,63	0,62	**0,84**	50	50
Sugar beet	18		**18**	0,81		**0,71**	1	99
Cassava	48	**48**	51	0,93	0,93	**0,96**	83	17
Sunflower	25	43	**22**	0,93	0,88	**0,93**	25	75
Soybean	34	36	**33**	0,95	**0,94**	0,93	32	68
Groundnut	31	33	**19**	0,84	0,82	**0,97**	81	19
Rapeseed	54	133	**39**	0,85	0,14	**0,91**	16	84

Bold values indicate which rule determining sowing date results in a closer agreement. Indices of agreement are only shown if the number of cells in which a specific rule for determining the sowing date is applied is > 1% of all cells. Grid cells with a crop area smaller than 0.001% of the grid area are not considered in the calculations.

* indices of agreement without Russia

2.4. DISCUSSION

Non-climatic reasons can considerably affect the timing of sowing. They arise from social attitudes and customs, religious traditions and the demand for certain agricultural products (Gill, 1991). In addition, agronomic practices, technological changes, and farm size can influence the timing of sowing. Depending on crop rotation, sowing can be affected by the harvest of the preceding crop (Dennett, 1999), and available labour and machinery, depending on farm size, determine whether sowing can be completed in the desired time period (Kucharik, 2006). The timing of sowing may also be influenced by the weather later in the growing season, e.g. in order to avoid possible dry spells during certain stages of crop development that are relatively sensitive to drought stress. Information on these technological and socio-economic conditions and their influence on the timing of sowing is scarce at global scale and has therefore not been considered in this study. The results of our study (Figure 2-4 and Figure A-1 to Figure A-11) show, however, that close agreement between simulated and observed sowing dates for large parts of the Earth for wheat, rice, millet, soybean, sugar beet and sunflower, as well as for pulses and maize in temperate regions, can be realized based on climatic conditions only. For most crops, the disagreement between simulated and observed sowing dates is only 1 month or less for the largest part of the global total cropping area (Figure 2-4b). At least 80% of the global cropping area displays a disagreement of less than 2 months (except for rapeseed, Figure 2-4b). However, some regions show mediocre or poor agreement, between simulated and observed sowing dates. The agreement is especially poor in tropical regions, where, despite a possible seasonality, climatic conditions are favourable throughout the year and in regions characterized by multiple cropping systems. Furthermore, agreement is poor in temperate regions, where both spring and winter varieties of wheat and rapeseed are grown, and in regions where observations are lacking or have been replaced or adjusted in MIRCA2000.

In the sections below the most likely reasons for strong disagreements are identified in example regions. Reasons can be limitations and uncertainties in MIRCA2000 e.g.: the spatial scale of MIRCA2000 or data gaps; uncertainties in our methodology e.g.: the usage of one global temperature threshold for sowing temperatures, which is known to vary between regions (Sacks *et al.*, 2010), or the application of specific crop management techniques e.g. multiple cropping systems.

Pulses and groundnuts in multiple cropping systems

The poor agreement between simulated and observed sowing dates for pulses in Southeast Asia, India, West and East Africa and Southeast Brazil, and for groundnuts in India (Figure A-10a), originates from a mismatch in production systems assumed.

In these regions, it is common practice to grow pulses and groundnuts in multiple cropping systems. In the south-eastern region of Brazil, with rainy seasons long enough for a multiple cropping system of maize and beans, bean is sown in combination with maize or after maize has been harvested (Woolley *et al.*, 1991). In West and East Africa, cowpea is largely grown as a second crop in multiple cropping systems with maize or cassava (in humid zones) and millet (in dry zones) (Mortimore *et al.*, 1997). These patterns are reflected in MIRCA2000. In contrast, we have assumed only single-cropping systems, so that sowing of pulses and groundnut starts at the beginning of the wet season, i.e. too early in comparison to the observations. Where cowpea is grown as a single crop, as in coastal regions of East Africa (Mortimore *et al.*, 1997), there is close agreement with the observed sowing dates (Figure A-5a).

The deviations in India for pulses (Figure A-5a), and for groundnut in western India (Figure A-10a), are associated with the occurrence of multiple cropping systems. Here, cowpea is grown in mixtures with sorghum and millet (Steele & Mehra, 1980) and groundnuts may be grown in the dry season following rice, often under irrigation (Norman *et al.*, 1995b).

Maize in multiple cropping systems in Southeast Asia

In Southeast Asia, as well as in China, a large number of crops may be grown on the same plot. According to Portmann *et al.* (2010), this indicates high land use intensities with multiple cropping systems. Intensive rice and wheat production are common practice in Asia (Devendra & Thomas, 2002), and maize has a subsidiary place in some of the Asian cropping systems as a second crop following the wet-season rice crop (Norman *et al.*, 1995b). This rice-maize multiple cropping system is covered by MIRCA2000, e.g. in China and Burma. As a consequence, the simulated growing period of maize starts earlier in the year than the observed growing period (Figure A-3a).

Wheat and rapeseed in temperate regions

The poor agreement for wheat and rapeseed in temperate regions of Russia, Australia and small parts of Europe (Figure A-1a and Figure A-11a) is the result of disagreement between the simulated and observed varieties of wheat and rapeseed.

In Russia, MIRCA2000 overestimates the share of winter wheat (Portmann *et al.*, 2010), because the cropping calendar for Russia is partly derived from the cropping calendars from Ukraine, Norway and Romania, where mainly winter wheat is grown (Portmann *et al.*, 2008). In contrast, we exclude winter wheat in Russia because temperatures drop below 12°C before 15 September, and consequently spring wheat is simulated in Russia. This is in line with the cropping calendar from USDA, which reports in addition to winter wheat, large areas of spring wheat in Russia (U.S. Department of Agriculture, 1994). In other temperate regions the agreement between simulated and observed sowing dates is good with only one month deviation and simulated sowing dates are similar to that shown in Bondeau *et al.* (2007).

For rapeseed in southern and eastern Australia, our rules simulate sowing dates in May and June (Figure A-11b), whereas MIRCA2000 reports a sowing date in December (Figure A-11c). However, in line with the simulations, West *et al.* (2001) and Robertson *et al.* (2009) confirm that rapeseed is grown as a winter crop, starting in May and June in Australia. In Europe, winter rapeseed is also the dominant cultivar due to its higher yield levels. Sowing dates of winter rapeseed in southern Europe can be extended from mid August to early September, as indicated by Booth & Gunstone (2004) and USDA (1994), which is in line with the simulated sowing dates in countries like, e.g., Spain, France, Hungary, Ukraine and Romania (Figure A-11b). MIRCA2000, however, indentifies spring rapeseed sown in May in those countries.

Cassava in multiple cropping systems

MIRCA2000 reports that in China, Thailand and Vietnam, cassava is sown in March as an early-ripening variety. In China, farmers plant cassava from February to April before the rainy season starts in order to use the cover of cassava plants to avoid soil losses due to the impact of heavy rains (Yinong *et al.*, 2001). Planting before the onset of the wet season may also avoid damage from pests (Evangelio, 2001). These practices explain the differences in southern China and Southeast Asia between observed and simulated sowing dates (Figure A-7a), because the simulated sowing dates are associated with the main wet season starting in May to July, not with the agronomic practices described in the literature.

Specific climatic conditions in temperate regions

Other examples of differences between observed and simulated sowing dates occur in European countries, partly in countries which are characterized by a Mediterranean climate. For sugar beet, both MIRCA2000 and our simulations indicate mainly spring-sowings in the Mediterranean region. However, the Mediterranean climate is characterized by mild winters and winter rainfall. In those regions, sugar beet is therefore sown in autumn, avoiding the high temperatures and high evapotranspirational demand of summer (Castillo Garcia & Lopez Bellido, 1986; Elzebroek & Wind, 2008; Rinaldi & Vonella, 2006). The effect of this specific climatic condition on sowing dates is not reflected in MIRCA2000, or in our simulations.

Limitations of MIRCA2000

Large differences between observed and simulated sowing dates occur in countries characterized by strong climatic gradients, associated with the size of countries (e.g. Russia, DR Congo, Mexico), or to large climatic variability, associated with large differences in elevation (e.g. Kenya). These gradients and variability influencing sowing dates are captured in our methodology, but not in MIRCA2000, where sowing dates for one spatial unit (country or sub-national unit) are assigned to grid cells of 0.5° by 0.5°. An example is the large difference between observations and simulations in the southern part of the DR Congo, where in MIRCA2000 missing observations were replaced by the cropping calendar from the neighbouring country Rwanda (Portmann *et al.*, 2008). While this procedure might be adequate for the northern parts of the DR Congo which are characterized by the same bimodal seasonal rainfall distribution, it is not adequate for the southern parts, where the main wet season does not start until November/December (McGregor & Nieuwolt, 1998).

Deficiencies in simulated sowing dates may strongly influence results of applications of the sowing date algorithm, depending on application and model used. A deviation of sowing dates by 2 or 3 months (e.g. sunflower in France, sugar beet in Spain, soybean in northern USA, or maize in Europe, see Figure A-1 to Figure A-11 in Appendix A) could already strongly affect the results of crop model applications, e.g. the assessment of crop evapotranspiration and crop virtual water content. The level of agreement per crop and region is therefore depicted in Appendix A, which allows for a more detailed evaluation of when to use our sowing date algorithm with caution.

2.5. CONCLUSIONS

This study presents a novel approach for deterministically simulating sowing dates under rainfed conditions for various annual field crops. We show that sowing dates for large parts of the Earth can be satisfactorily estimated from climatic conditions only. Close agreement is achieved between simulated and observed sowing dates, although substantial deviations occur in: (1) tropical regions and (2) regions with high land-use intensity and multiple cropping systems. Even if those regions show seasonality in temperature or precipitation, climatic conditions can be suitable throughout the year for crop growth. In both types of regions, climatic conditions are of minor importance for the timing of sowing, instead it is determined mainly by other criteria such as the demand for special agricultural products, availability of labor and machines, and religious and/or social traditions (Gill, 1991; Kucharik, 2006). Furthermore, certain cropping practices and crop rotations are applied in order to avoid pests and disease infestations. These agronomic practises cannot be considered in our methodology due to lack of information at global scale. Differences between simulated and observed sowing dates in regions without precipitation and temperature seasonality have little impact on the computed crop yield in global crop growth models such as LPJmL. Sowing date deviations of one month or more, in locations with temperature and precipitation seasonality may lead to substantially different simulated crop yields. In the LPJmL model with the currently implemented cultivars, sowing dates simulated with the presented methodology are within the most productive cropping window for almost all locations displayed in Figure B-1. However, the interaction of sowing dates, management options, and cultivar characteristics will have to be evaluated further.

Our methodology is explicitly developed for the global scale. Climate and soil characteristics, as well as agricultural management practices can vary considerably among regions. If applied at smaller scales, parameter values as proposed here should be adapted, e.g. the temperature threshold for sowing can show spatial variability (Sacks *et al.*, 2010), and important socio-economic and technical drivers should be considered to attain higher accuracy. In addition, if reliable daily minimum and maximum temperature and precipitation data are available, rules should adapted in order to consider avoidance of damage by frost or extreme high temperature. At global scale, our methodology is suitable for simulating sowing dates for global crop growth models. In our methodology, we are able to apply current and future climate input data. We are therefore able to account for some possible global responses by farmers to climate change in their sowing dates.

2.6. ACKNOWLEDGEMENTS

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2.7. AUTHORS´ CONTRIBUTION

Authors´ contribution was as follows: K.W., L.vB, A.B. and C.M. conceived the idea of simulating sowing dates from climatic conditions and from the intra-annual variability of temperature and precipitation, K.W. and C.M. wrote code and prepared MIRCA2000 for validation, K.W. did the model runs, derived the temperature thresholds for sowing, and prepared the figures, L.vB carried out the sensitivity analysis, and L.vB and K.W. did literature research, wrote the manuscript, and prepared the supporting material. All authors were involved in developing the methodology and discussing the model outputs.

3. Adaptation to climate change through the choice of cropping system and sowing date in sub-Saharan Africa

Our aim is to show the distribution of multiple cropping systems in sub-Saharan Africa and analyse the susceptibility of traditional sequential cropping systems to climate change. They provide more harvest security for farmers and allow for crop intensification. Furthermore, the occurrence of multiple cropping systems will influence ground cover, soil erosion, albedo, soil chemical properties, pest infestation and the carbon sequestration potential. Comparing their productivity under climate change to crop yields from alternative management strategies like growing a single crop only or adapting the sowing date allows us to identify the most suitable management strategy.

We identify the traditional sequential cropping systems composed of two crops following one after another in ten sub-Saharan African countries from a dataset containing more than 8600 household surveys. We design six different management scenarios for adaptation to climate change and estimate crop yields for each of them. The dynamic global vegetation model for managed land LPJmL (Bondeau *et al.*, 2007) is used to simulate crop yields under current and future climatic conditions from three climate models for the SRES A2 and constant atmospheric CO_2 concentrations.

We found that 13 different traditional sequential cropping systems were most frequently applied in the study area. In 35% of all administrative units, at least one sequential cropping system, mostly with groundnut or maize, is applied. Aggregated mean crop yields in sub-Saharan Africa decrease by 6 % to 24 % due to climate change depending on the climate model and the management strategy. The crop yield decrease is typically weakest in sequential cropping systems and if farmers adapt the sowing date to a changing climate. Crop calorific yields in single cropping systems only reach 45 to 55 % of crop calorific yields obtained in sequential cropping systems. Southern and Western Africa are the most heavily impacted regions with declines in crop yield of up to 45 % and 18 % respectively depending on the management scenario. As an exception, some traditional sequential cropping systems in Kenya and South Africa gain by at least 25 %. In Cameroon, Kenya, South Africa and Zimbabwe some of the traditional sequential cropping systems are more resilient to negative climate change impacts than the highest-yielding sequential cropping systems. As the farmers' choice of adequate crops, cropping systems and sowing dates can be an important adaptation strategy to climate change these management options should be considered in climate change impact studies on agriculture.

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3.1. INTRODUCTION

The number of undernourished people remains highest in sub-Saharan Africa compared to other world regions and population will be more than doubled in 2050 compared to 2000. Among effective strategies like fighting poverty, stabilizing economies and ensure access to food, increased food production in smallholder agriculture will be a key strategy for fighting hunger (FAO, 2008). Agricultural production can be increased by expanding agricultural land and by increasing the intensification of crop production through higher crop yields and higher cropping intensities. The cropping intensity in less-developed countries can be increased by about 5-10 % during the next 35 years if adequate amounts of input are available (Döös & Shaw, 1999). Multiple cropping systems allow for this intensification by growing two or more crops on the same field either at the same time or after each other in a sequence (Francis, 1986b; Norman *et al.*, 1995a). They already are common farming systems in tropical agriculture today (Table 3-1). In multiple cropping systems the risk of complete crop failure is lower compared to single cropping systems and monocultures providing a high level of production stability (Francis, 1986a). Furthermore the second crop in a sequence may benefits from an increased amount of nitrogen derived from fixation (Bationo & Ntare, 2000; Sisworo *et al.*, 1990) or phosphorous from deep-rooted species (Francis, 1986a) as well as from decreased disease pressure (Bennett *et al.*, 2012) which helps to reduce the use of mineral fertilizer and pesticides. Cropping intensity is not only important in terms of agricultural production; the duration crops cover the soil will also influence albedo, ground cover, carbon sequestration potential and soil erosion (Keys & McConnell, 2005). In sub-Saharan Africa, multiple cropping systems mostly consist of cereal-legume mixed cropping dominated by maize, millet, sorghum and wheat (Van Duivenbooden *et al.*, 2000). Maize- and cassava-based mixed cropping systems are common in humid East and West Africa, whereas millet-based mixed cropping is widely applied in dry East and West Africa (Francis, 1986b). Intercropping is the traditional and most frequently applied multiple cropping system in sub-Saharan Africa, however sequential cropping and mixed sequential cropping systems are also common indigenous management practices (Table 3-1).

Table 3-1 Definition of terms used in this study.

Term	Definition, Description
single cropping	A cropping system with only one crop growing on the field (Bennett *et al.*, 2012). Interchangeable with monoculture or continuous cropping.
sequential cropping	A cropping system with two crops grown on the same field in sequence during one growing season with or without a fallow period. A specific case is double cropping with the same crop grown twice on the field.
mixed sequential cropping	A cropping system with two intercropping systems grown on the same field in sequence during one growing season with or without a fallow period.
growing period	The period of time from sowing to maturity determined by the sum of daily temperatures above a crop-specific temperature threshold = phenological heat unit sum (PHU).
growing season	The period of time in which temperature and moisture conditions are suitable for crop growth, in the sub-tropical and tropical zones determined by the start and end of the main rainy season.
multiple cropping	“ […] may refer to either growing more than one crop on a field during the same time (intercropping), after each other in a sequence (sequential cropping) or with overlapping growing periods (relay cropping)” (Francis, 1986b; Norman *et al.*, 1995a). Examples in sub-Saharan Africa are: groundnut-millet succession in the northern part of central Africa (de Schlippe, 1956) wheat-chickpea succession in Ethiopia (Berrada *et al.*, 2006) maize double cropping in western Nigeria (Francis, 1986b) cowpea-maize sequence cropping in the moist Savannah zone of northern Nigeria (Carsky *et al.*, 2001), soybean and wheat sequences in Zimbabwe (Beets, 1982), sorghum and pigeonpea in northern Nigeria (Francis, 1986a), sorghum double cropping in southern Guinea and Savannah zones of West Africa (Kowal & Kassam, 1978).

Agricultural activities and consequently the livelihoods of people reliant on agriculture will be affected by changes in temperature and precipitation conditions in large parts of sub-Saharan Africa (Boko *et al.*, 2007; Christensen *et al.*, 2007; Müller *et al.*, 2011). Under climate change, many areas in sub-Saharan Africa are likely to experience a decrease in the length of the growing season, while in some highland areas rainfall changes may lead to a prolongation of the growing season (Thornton *et al.*, 2006). The degree of climate change impacts on agricultural production differs between crops (Challinor et al., 2007; Liu et al., 2008; Schlenker & Lobell, 2010; Thornton et al., 2011) and agricultural systems (Thornton *et al.*, 2010). Therefore the farmers' choice of an adequate cropping system and crop cultivar, especially in precipitation-limited areas, might be an important adaptation strategy to changing climate conditions (O´Brien *et al.*, 2000; Thomas *et al.*, 2007). Lobell *et al.* (2008) note that the identification of practicable adaptation strategies for cropping systems should be prioritized for regions impacted by climate change. However, few studies investigate the impact of climate change on agriculture in sub-Saharan Africa considering the cropping system applied or make an effort to identify the least impacted cropping systems. The study of Thornton *et al.* (2009) is an exception, analysing crop yield response to climate change of a maize-bean cropping sequence in East Africa under which beans grow in a separate second growing season.

Analysing different multiple cropping systems in a climate impact study for sub-Saharan Africa requires a dataset reporting their spatial distribution in the region, which to our knowledge is not available. Some crop calendars available at the global (Portmann *et al.*, 2010; Sacks *et al.*, 2010) or African scale (FAO, 2010) report the growing periods of individual crops but lack reporting calendars for multiple cropping systems, while some others only cover Asian regions (Frolking et al., 2006; Frolking et al., 2002). Fischer *et al.* (2002b) identified potential double and triple cropping zones by comparing temperature and moisture requirements of four crop groups with climatic conditions worldwide. Thornton *et al.* (2006) developed a classification for agricultural systems in Africa by combining a global livestock production classification system, a farming system classification, and global land cover maps. Both datasets do not report the crop cultivars or the cropping systems.

The knowledge about the spatial distribution of multiple cropping systems needs to be expanded by more detailed information on the sub-national level. We analyse a household survey (Dinar *et al.*, 2008) carried out in 385 districts and provinces containing more than 8600 households in ten countries of sub-Saharan Africa to fill this gap. From this survey we are able to identify the traditional rainfed sequential cropping systems with two crops grown within one year. As these are advantageous management strategies because they allow for risk spreading and increased crop productivity, we test their susceptibility to future climatic conditions in comparison to alternative management strategies by simulating crop yields with the dynamic global vegetation model for managed land LPJmL (Bondeau *et al.*, 2007). We analyse the ability of each management strategy to maximize future crop productivity or lower negative impacts from climate change on crops. We perform this analysis in locations where sequential cropping systems are already applied by local farmers today and also for the entire region of sub-Saharan Africa in order to estimate potential benefits.

3.2. MATERIALS AND METHODS

Input data for current and future climate

To describe current climatic conditions, we used time series of monthly temperature and precipitation as well as the number of wet days from the climate database CRU TS 3.0 (Mitchell & Jones, 2005) for the 30-year period 1971 to 2000 on a spatial resolution of 0.5° x 0.5°. Future climatic conditions for the 30-year period 2070-2099 were projected from the three Global Circulation Models (GCMs) ECHAM5 (Jungclaus et al., 2006), HadCM3 (Cox et al., 1999), and CCSM3 (Collins et al., 2006) under the SRES A2 emission scenario. As there is little consistency between GCM projections on precipitation (Boko et al., 2007) they were chosen to show a wide range of possible future precipitation patterns (Fig. 1). The monthly mean temperature and precipitation sums from these three GCMs were interpolated to a finer spatial resolution of 0.5° x 0.5° using bilinear interpolation and smoothed using a 30-year running mean. The temperature and precipitation anomalies from each GCM were calculated relative to the 1971-2000 average climate from CRU TS 3.0 and were then applied to this baseline while preserving observed variability (Gerten et al., 2011). Daily mean temperatures were obtained by linear interpolation between mean monthly temperatures, and daily precipitation data was provided by a weather generator which distributes monthly precipitation to the number of observed wet days in a month, considering the transition probabilities between wet and dry phases (Geng *et al.*, 1986; Gerten *et al.*, 2004). We kept the number of wet days constant at their average number from the time period 1971-2000. Geng *et al.* (1986) confirms that the rainy days as well as the amount of precipitation generated from this procedure are in general very close to observations in different environments. In this analysis we keep atmospheric CO_2 concentrations constant at 370 ppm. Increasing atmospheric CO_2 concentrations can increase the productivity of plants (especially C_3 plants), but the effectiveness on increasing crop yields is uncertain (Long *et al.*, 2006; Tubiello *et al.*, 2007) and does require adaptation in management (Ainsworth & Long, 2005).

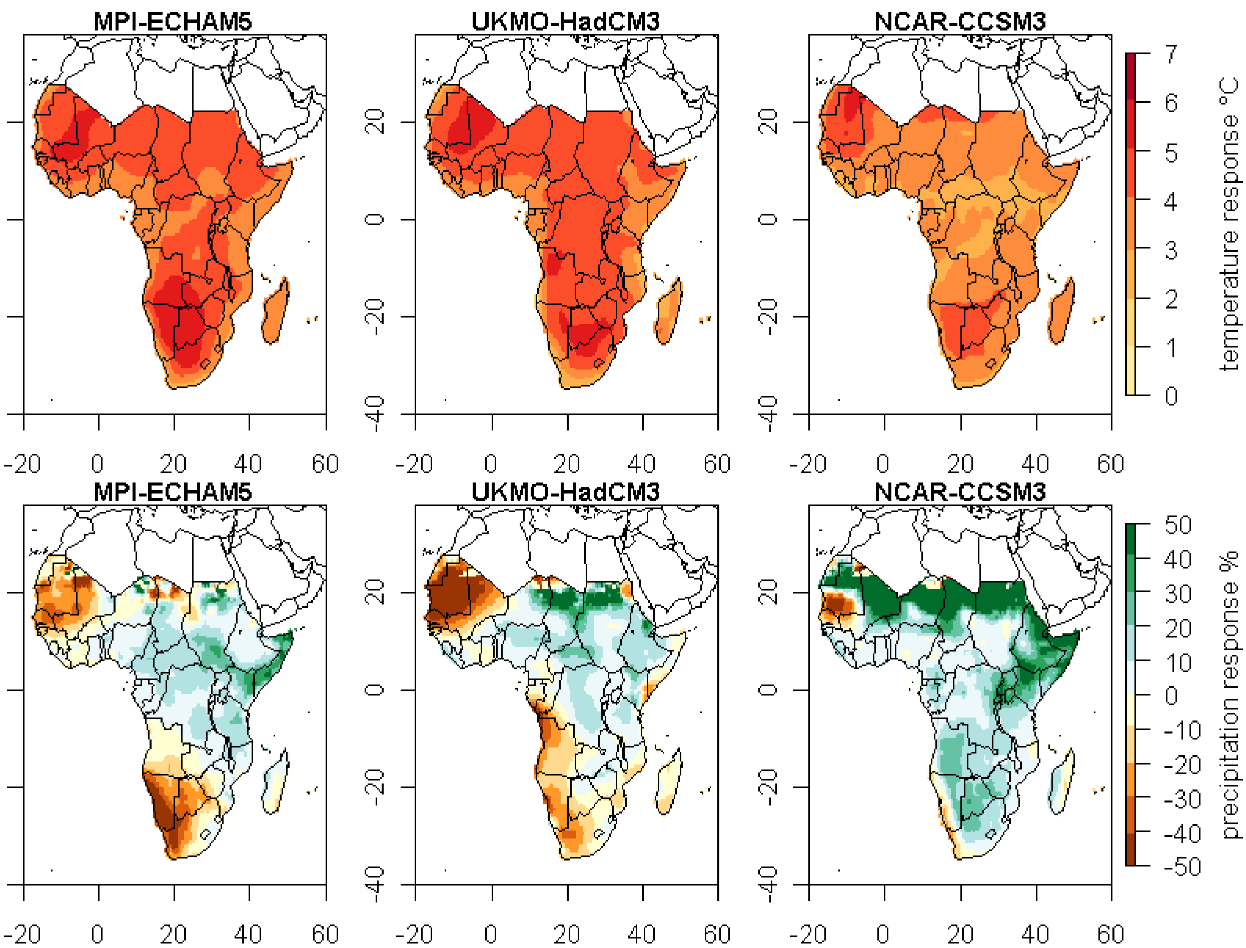

Figure 3-1 Change in annual mean temperature and annual mean precipitation from 1971-2000 to 2070-2099 projected from three GCMs under the SRES A2. Brown and green colours in the lower three panels indicate a decrease or an increase in annual mean precipitation respectively.

Household survey

A subset of a household survey (Dinar *et al.*, 2008) containing 8697 households in ten sub-Saharan African countries (Burkina Faso, Cameroon, Ethiopia, Ghana, Kenya, Niger, Senegal, South Africa, Zambia, and Zimbabwe) is used to calculate the growing periods (Table 1) of crops grown in different cropping systems. This dataset is the product of a World Bank/Global Environmental Facitily project that was coordinated by the Centre for Environmental Economics and Policy for Africa (CEEPA) at the University of Pretoria, South Africa.

Half of the households are small-scale farmers, the other half are medium- or large-scale farmers. Each farm type was surveyed in each country, but in Zimbabwe, Zambia and Ghana more than 80 % of the households are smallholders. In contrast, 73 % of all households in Senegal belong to a large-scale farm. The household survey reports sowing and harvest dates from 56 crops which are grown on up to three plots in up to three seasons within 12 months. Up to six crops are grown simultaneously on a plot. For each of these countries, data from 416 to 1087 households in 17 to 61 representative sample units (district or province) were collected for only one farming season (2002/2003 or 2003/2004),. Sowing and harvest dates were reported on a daily, weekly or monthly basis and were converted into a uniform date specification using the day of the year. For weekly data we assumed the first day of the week, for monthly data the 15th day of the month. The length of the growing period in days for nine crops (cassava, cowpea, groundnut, maize, millet, rice, soybean, sunflower, and wheat) as well as for a group of other crops was derived from these daily sowing and harvest dates. As harvest sometimes occurs shortly after sowing but the year of sowing and harvest events is not always reported, we assume a minimum length of 2 months for the growing period (6 months for cassava).

Identification of sequential cropping systems

We identify the sequential cropping and single cropping systems applied within one farming season in a sample unit by combining the data of crops and their growing periods in each plot and season. We assume single cropping systems if only one single crop is reported to grow on a plot (Figure 3-2B) or if more than one crop is grown on a plot but the sum of their growing periods is larger than 365 days and/or their growing periods overlap by more than 15 days (Figure 3-2C, Figure 3-2A), i.e. the growing period a crop is not restricted by the occurrence of other crops on that plot. In contrast, we assume sequential cropping systems if two crops are reported to be planted one after another without overlaps of more than 15 days and if their growing periods sum up to less than 365 days (Figure 3-2D-G), i.e. the growing period of a crop here is restricted by the occurrence of the associated crop on the plot.

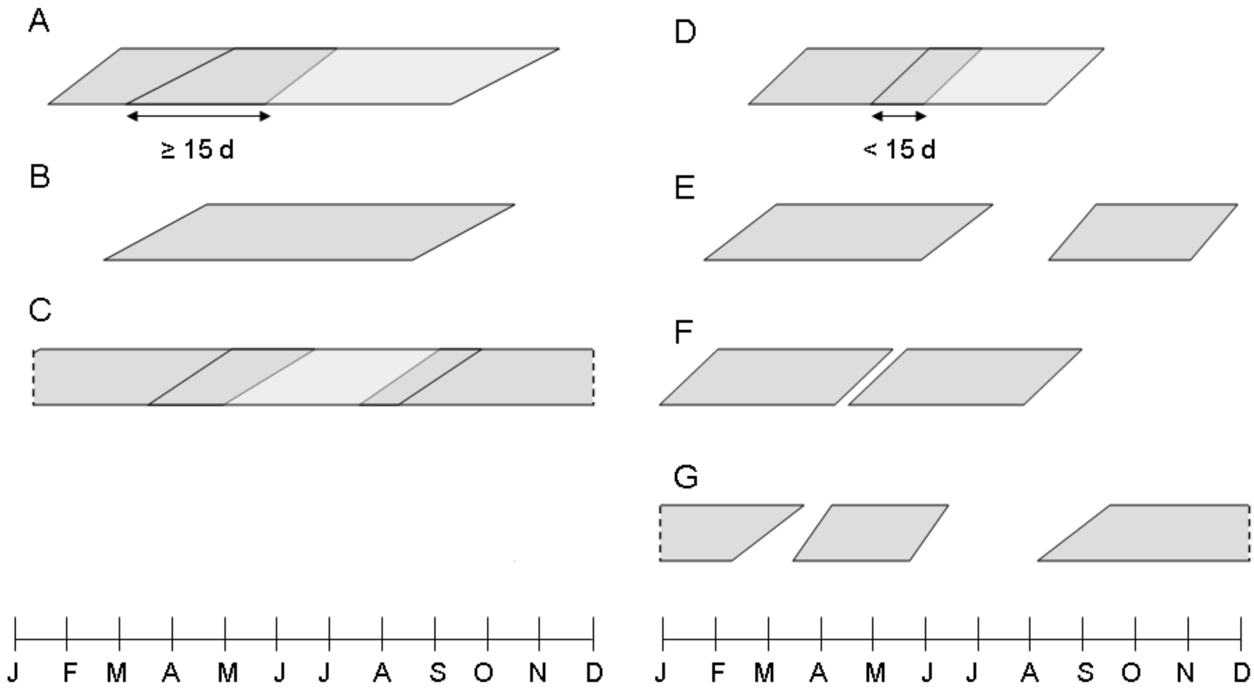

Figure 3-2 Scheme of possible timing and length of growing periods of crops in single cropping systems (A-C) and sequential cropping systems (D-G) according to the definition used in this study. A: two single cropping systems with large overlap, B: one single cropping system, C: two single cropping systems, one spanning the turn of the year and with the sum of the growing periods exceeding 365 days, D: sequential cropping system with small overlap, E: sequential cropping system with long fallow period, F: sequential cropping system with short or no fallow period, G: sequential cropping system spanning the turn of the year with sum of growing periods below 365 days.

An overlap of 15 days corresponds to the maximum possible error in sowing and harvest dates owing to the conversion from monthly to daily data. We only consider rainfed systems in this study because irrigation systems are rarely available in sub-Saharan Africa. If various sequential cropping systems exist within a district, we identify the most frequently applied sequential cropping system in a district and assume this system to be the traditionally applied sequential cropping system. Based on the distance between the centre coordinates of the districts and those of the 0.5° x 0.5° grid cells, the sequential cropping systems found in a district are allocated to the closest grid cell. If a district covers more than one grid cell the sequential cropping systems are distributed to all corresponding grid cells.

Management scenarios for adaptation

Farmers choose a cropping system according to economic market trends, consumer demands, availability of inputs such as seeds, fertilizer and pesticides, agronomy traditions as well as current land-use, climatic conditions and soil properties (Bennett *et al.*, 2012; Castellazzi *et al.*, 2008) in order to maximize their yield and profit and/or to minimize the risk of crop failure through diversification. Rainy seasons long enough for growing two crops in a sequential cropping system allow for intensification and more harvest security for farmers because crop yields are obtained two or more times a year (Andrews & Kassam, 1976). If necessary, farmers respond to perceived changes and variability in climate by e.g. changing the sowing date of cultivated crops or switching to a more suitable crop or crop cultivar with a different growing period, heat tolerance or drought resistance. These strategies were already observed in Tanzania (O´Brien *et al.*, 2000), semi-arid West Africa (Mation & Kristjanson, 1988), and South Africa (Benhin, 2006). It can thus be expected that farmers will adapt their traditional cropping system to a changing climate to some extent. We define three management scenarios, analyzing different cropping system with the aim of comparing changes in crop yields with changing climate of the 21st century in order to find the most suitable strategy:

TS: Traditional sequential cropping system: The baseline strategy. Farmers grow the sequential cropping system most frequently applied in their district composed of two short-growing crop cultivars.

SC: Single cropping system: Farmers only grow one long-growing cultivar of the first crop of the traditional sequential cropping system.

HS: Highest-yielding sequential cropping system: Farmers grow the sequential cropping system composed of two short-growing crop cultivars with the highest yields.

Sowing dates in these scenarios change dynamically, with changes in the start of the main rainy season allowing for inter-annual variability. In order to assess the importance of adapting sowing dates to changing climate or weather conditions three additional scenarios are designed in which the sowing dates are kept constant with the simulated sowing dates in the first simulation year 1971.

TSco: Traditional sequential cropping system as described above with constant sowing dates.

SCco: Single cropping system as described above with constant sowing dates.

HSco: Highest-yielding sequential cropping system as described above with constant sowing dates.

Accordingly, each of the six management scenarios is a combination of a specific cropping system and sowing date setting, as these are important management options for farmers.

We assume that farmers prefer short-growing crop cultivars in sequential cropping systems in order to reduce the risk of crop failure in the second half of the growing season (Table 1) or, alternatively, long-growing crop cultivars in single cropping systems in order to increase the yield. Sequential cropping systems are advantageous farming systems but cannot be applied if the growing season is too short. In this case a single cropping system may be the most suitable cropping system. Adapting sowing dates to shifts in the start of the rainy season ensures optimal growing conditions and low risk of drought at important crop growth stages and, therefore, allows for better use of rainwater and potentially increased crop yields (Van Duivenbooden *et al.*, 2000).

Dynamic global vegetation model for managed land LPJmL

LPJmL is a process-based global vegetation model for natural and agricultural vegetation, simulating biophysical and biogeochemical processes as well as productivity and yield of the most important crops (Bondeau *et al.*, 2007; Sitch *et al.*, 2003). Carbohydrates from photosynthesis are allocated to different crop organs at daily time steps depending on the phenological stage of the crop and environmental conditions. To simulate the phenological development of a crop, the heat unit theory is applied (Bondeau *et al.*, 2007). Heat units (in degree-days [°Cd]) are calculated from daily temperatures above a base temperature (Table 2) and are summed over all phenological stages (potential heat unit sum, PHU [°Cd]). This empirically derived quantitative measurement describes the effect of air temperature on the growth of crops (Boswell, 1926) and reflects the length of a crop's growing period.

Temperature and water stress influence crop development and growth (Bondeau *et al.*, 2007). Increasing temperatures lead to a shortened growing period because crops reach maturity earlier in the year and crop yields potentially decrease. Stress due to extreme temperatures does not damage the crop irreversibly in the model, but temperatures beyond the optimal temperatures for photosynthesis reduce productivity. A water stress factor is calculated from the ratio of water supply through plant water uptake from the soil and atmospheric water demand (Sitch *et al.*, 2003) and influences leaf growth (Bondeau *et al.*, 2007). We extended this approach to also account for changes in root growth in response to water stress (Appendix C). Water stress effecting leaf and root growth negatively might occur more frequently in the second crop cycle because water stored in the soil was already consumed by the preceding crop.

It is possible to simulate different crop cultivars with LPJmL for wheat and rapeseed (spring and winter cultivar), as well as for maize and sunflower (temperate and tropical cultivar) by varying the PHU (Bondeau *et al.*, 2007). We extend this approach by calculating PHUs for a short-growing crop cultivar grown in sequential cropping systems (PHU_{seq}) and a long-growing crop cultivar grown in single cropping systems (PHU_{sin}) from observed growing periods and daily temperatures in sub-Saharan Africa. The base temperatures are taken from LPJmL (Bondeau *et al.*, 2007) for groundnut, millet, rice, soybean, sunflower and wheat and from SWAT (Neitsch *et al.*, 2002) for cassava, cowpea and maize (Table 2).

The start of the growing season in subtropical and tropical environments is determined by the start of the main rainy season and is simulated dynamically in LPJmL from monthly climatology (Waha *et al.*, 2012). This procedure follows the commonly used approach of identifying the onset and end of the rainy season with a criterion based on the average rainfall or radiation of a specific period, e.g. 5 days (Marengo *et al.*, 2001; Omotosho *et al.*, 2000; Wang & Ho, 2002). In slight contrast to the methodology described in Waha *et al.* (2012) for the global scale, this criterion is defined here as the three-month averaged ratio between precipitation and potential evapotranspiration:

$$\frac{P}{PET} = \frac{1}{12} \times \sum_{i=1}^{12} \sum_{m=i}^{m+3} \frac{P}{PET}_m$$

where P/PET is the mean three-month averaged precipitation-to-potential evapotranspiration ratio, P/PET_m is the precipitation-to-potential evapotranspiration ratio of each individual month m. Potential evapotranspiration is calculated in LPJmL using the Priestley-Taylor equations (Priestley & Taylor, 1972) with a Priestley-Taylor coefficient of 1.391 (Gerten *et al.*, 2004).

Consequently, the onset of the growing season is defined as the first month in a three-month period where precipitation-to-potential-evapotranspiration ratios exceed the mean ratio. Within this month the growing period of an individual crop starts at the first wet day with daily precipitation above 0.1mm; in sequential cropping systems the following crop is assumed to be sown immediately after the harvest of the first crop. In temperate environments such as parts of South Africa, the start of the growing season is determined by daily temperature as described in Waha *et al.* (2012). The start of the main rainy season in sub-Saharan Africa as simulated here agrees well with the observed start of the main growing season derived from satellite data (Appendix D).

The growing period is limited to a maximum of 330 days allowing for a short fallow period between two consecutive years. The simulated harvested carbon in gC/m^2 is converted to crop yield in Mcal/ha to allow for a comparison between crops and cropping systems with:

$$Y_{Mcal} = \frac{H}{0.45} \times \frac{100}{DM} \times Cal \times 10^4$$

where Y_{Mcal} is the calorific yield in Mcal/ha, H the harvested carbon in gC/m², DM the crop-specific dry matter content in %, and Cal the crop-specific calorie content in Mcal/g fresh matter (Table 3-2). Dry matter content and calorie content of crop products are taken from Wirsenius (2000) and from FAO Food Balance Sheets (FAO, 2001). The overall crop yield in sequential cropping systems is the sum of two individual crop yields in Mcal/ha.

Management intensity in a cropping system is described by three parameters: the maximal attainable leaf area index, the maximal harvest index and a parameter scaling leaf-level biomass to field level as described in Fader *et al.* (2010). The management intensities per crop and country were chosen to match observed production levels of FAO in the 5-year-period 1999-2003 (Appendix E).

Table 3-2 Crop-specific parameters for estimating PHUs in single and sequential cropping systems and calculating fresh matter crop yields in kcal/ha.

	Parameters for estimating PHU_{sin} and PHU_{seq} in LPJmL $PHU_{sin} = \alpha + \beta T + \gamma P_{gs} + \delta PET_{gs}$ and $PHU_{gap} = \frac{PHU_{seq}}{PHU_{sin}}$											**Dry matter DM [c] and calorie content Cal [d]**	
Crop	Base temperature[a,b] [°C]	α [°Cd]	β [d]	γ [°Cd/ mm]	δ [°Cd/ mm]	R	R^2	Min PHU_{sin} [°Cd]	Max PHU_{sin} [°Cd]	N	PHU_{gap} [-] ‡	N	DM [%]	Cal [kcal/ g]
Cassava	14	-4910	327	0.5	-0.6	0.75	0.56	910	4510	213	0.67 ± 0.26 ***	50	35	1.09
Cowpea	14	-470	44	-0.2	0.9	0.58	0.34	740	1910	190	0.75 ± 0.21 ***	33	90	3.41
Groundnut	14	470	32	-0.2	0.4	0.48	0.23	1070	1990	336	0.99 ± 0.29 *	117	94	4.14
Maize	8	1740	0.1	-0.1	0.7	0.48	0.23	1880	3640	472	0.92 ± 0.21 ***	224	88	3.56
Rice	10	250	21	0	1.3	0.65	0.42	1450	2700	102	0.88 ± 0.19 *	16	87	2.80
Wheat	0	-390	146	0.8	-0.2	0.76	0.58	2180	4310	61	0.87 ± 0.34 *	26	88	3.34

[a] Bondeau *et al.* (2007), [b] Neitsch *et al.* (2002), [c] Wirsenius (2000), [d] FAO (2001).

‡ Values are means ± standard deviation for PHU_{gap}. Level of significance (*** p<0.001, ** p<0.01, and * p<0.05) is given for the hypothesis that $PHU_{seq} < PHU_{sin}$ (Wilcoxon signed-rank test).

Modelling the spatial variation of PHU_{sin} and PHU_{seq}

PHU_{sin} and PHU_{seq} are calculated by accumulating daily temperatures above a base temperature threshold (Table 3-2) summed over the growing period that is reported in the household survey. In order to estimate PHU_{sin} for each crop in each grid cell in sub-Saharan Africa, we use a multiple linear regression model between PHU_{sin} and climatic parameters in each grid cell. We found a correlation, although light, for maize and groundnut, between PHU_{sin}, mean annual temperature and moisture conditions during the growing season:

$$PHU_{sin} = \alpha + \beta T + \gamma P_{gs} + \delta PET_{gs}$$

where T is the annual mean temperature, P_{gs} the sum of monthly precipitation during the growing season, PET_{gs} the sum of monthly potential evapotranspiration during the growing season, and α, β, γ and δ are empirical parameters.

Precipitation and potential evapotranspiration represent the atmospheric water supply and water demand, respectively. Thus their ratio in the growing season represents the water availability during the period of high agricultural activity.

We compare PHU_{sin} and PHU_{seq} with the aim of verifying the assumption that farmers apply short-growing crop cultivars in sequential cropping systems and long-growing crop cultivars in single cropping systems. We test if PHU_{sin} is statistically greater than PHU_{seq} for each crop using the non-parametric Wilcoxon signed-rank test (Wilcoxon, 1945). In order to estimate PHU_{seq} for each crop in each grid cell, we derive a uniform crop-specific factor PHU_{gap} from the calculated PHU_{sin} and PHU_{seq} to account for the deviation between them:

$$PHU_{gap} = \frac{PHU_{seq}}{PHU_{sin}}$$

Theoretical potential of sequential cropping systems

In addition to the analysis of climate change impacts on crop yields in districts where sequential cropping systems are already grown, we apply a similar analysis to the entire region of sub-Saharan Africa that currently has growing periods larger than 5 months (Harvest Choice, 2011) to analyze the adaptation potential of sequential cropping systems. Crop yields from 13 sequential cropping systems and six single cropping systems are simulated with LPJmL and compared in all sub-Saharan Africa grid cells that are currently used for crop production following Fader *et al.* (2010).

3.3. RESULTS

Sequential cropping systems in sub-Saharan Africa

In 35 % of the surveyed districts one or more sequential cropping system exist, but only in seven out of ten surveyed countries and about 17 % of the districts sequential cropping systems are composed of crops included in our model. Figure 3-3 shows the distribution of the 13 traditional sequential cropping systems in the surveyed districts. The sequential cropping systems frequently applied are mostly based on groundnut and maize and to a smaller extent also on cassava, rice, wheat, and cowpea, but only few sequential cropping systems exist with sunflower or soybean, which are of minor importance in the surveyed households. In Eastern Africa all sequential cropping systems are based on maize, whereas in Southern Africa wheat-maize systems are additionally applied. Systems based on groundnut as the first crop can be found in Ghana and in Cameroon, which is the country with the highest diversity in sequential cropping systems. The highest-yielding among all 13 traditional sequential cropping systems are mostly based on maize (Table 3-3).

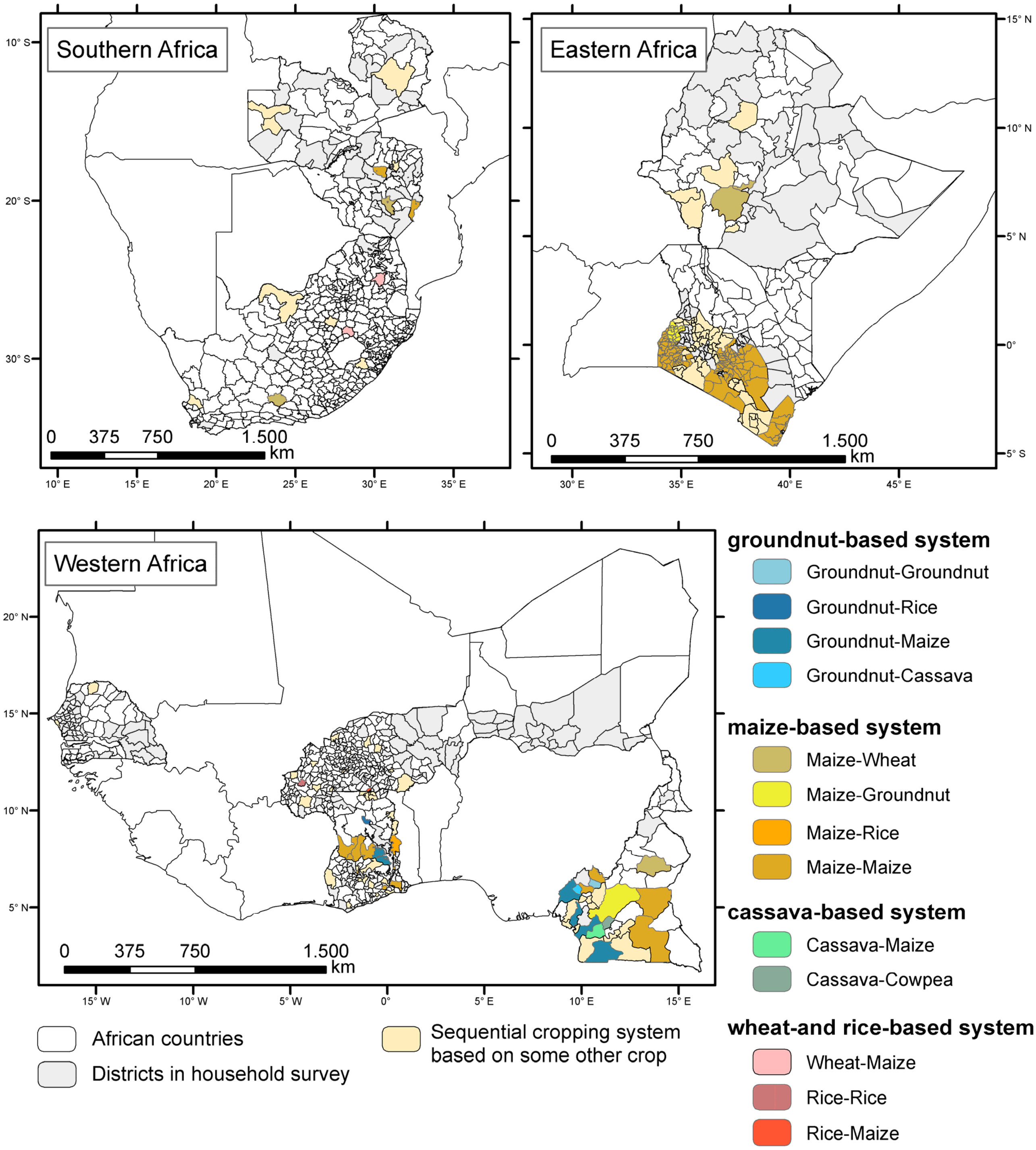

Figure 3-3 Most frequently applied rainfed sequential cropping systems in sub-Saharan Africa. The classification of sequential cropping systems used for legend titles is based on the first crop grown in the sequence.

Table 3-3 Highest-yielding rainfed sequential cropping systems in the period 1971-2000 in 63 districts in seven sub-Saharan Africa countries depending on the location within the country. Sequential cropping systems in Niger, Senegal and Zambia are based on some other crop than the crops in this study.

Country	System	Country	System
Burkina Faso	Maize-Rice, Rice-Rice	Ghana	Cassava-Cowpea
Cameroon	Wheat-Maize, Maize-Wheat, Maize-Maize, Cassava-Maize	Kenya	Wheat-Maize, Rice-Rice, Maize-Maize, Cassava-Maize, Cassava-Cowpea, Groundnut-Cassava, Groundnut-Groundnut
		South Africa	Wheat-Maize, Maize-Wheat, Cassava-Maize, Cassava-Cowpea
Ethiopia	Cassava-Cowpea	Zimbabwe	Wheat-Maize

Results of this analysis are derived by simulating crop yields from 13 sequential cropping systems found in the household survey.

Growing periods and PHUs of different crop cultivars

The lengths of the growing periods calculated from the household survey of most of the crops lie within the range of values found in the literature, except for cowpea, groundnut and maize (Table 3-4). The growing periods from the household survey and the corresponding PHUs differ significantly between single and sequential cropping systems as well as between crops (see level of significance and PHU_{gap} in Table 3-2). The results of the Wilcoxon signed-rank test indicate that PHU_{sin} significantly exceeds PHU_{seq} by 900 °Cd on average. The deviation between large PHU_{sin} and small PHU_{seq} per individual crop is significant as well and can be described by the crop-specific factor PHU_{gap}, which accordingly is less than 1 (Table 3-2).

Table 3-4 Time from sowing to harvest in months for different crop cultivars found in the household survey and in literature.

Crop	Household survey	Literature
Cassava	6 – 11	6 – 24 (Alves, 2002)
Cowpea	2 – 9 ½	1 ½ – 6 (FAO, 2010; Madamba *et al.*, 2006)
Groundnut	2 – 10 ½	2 ½ – 6 (Ntare, 2006; Schilling & Gibbons, 2002; Virmani & Singh, 1986)
Maize	2 – 9	2 ½ – 6 ½ (Badu-Apraku & Fakorede, 2006)
Rice	2 – 6 ½	3 – 7 (Badu-Apraku & Fakorede, 2006; Meertens, 2006)
Wheat	3 – 6	3 – 5 ½ (Belay, 2006; FAO, 2010; Rehm & Espig, 1991)

Using the multiple regression model to determine the heat sum requirements for phenological development, simulated growing periods from LPJmL differ from growing periods in the household survey: for wheat, rice and cowpea, simulated growing periods are on average 5 to 32 days shorter than the growing periods in the household survey, while those for groundnut, cassava and maize are on average 7 to 33 days longer than the growing periods reported in the household survey (Figure 3-4).

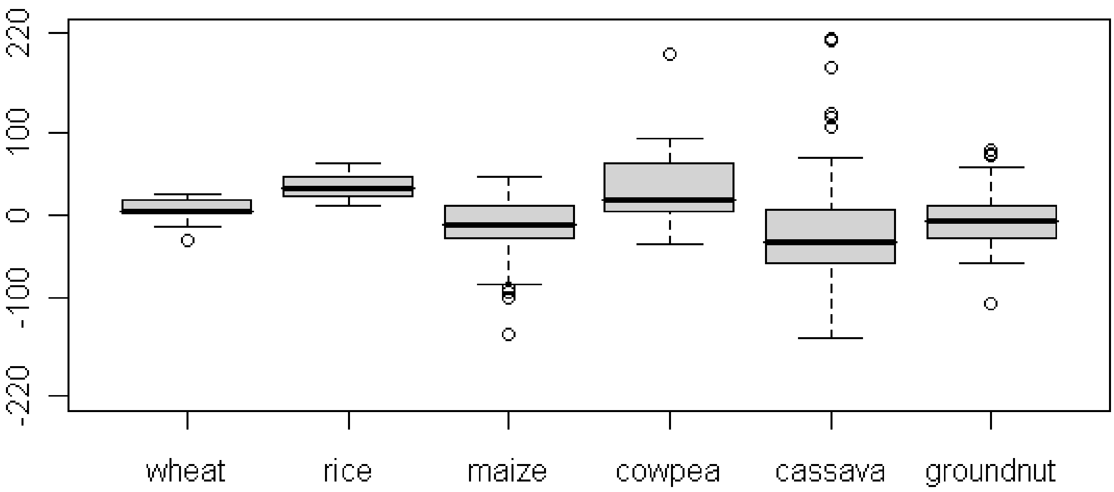

Figure 3-4 Deviations in days between simulated and observed length of growing period in 2002/03 in single cropping systems (observed – simulated). Each box stretches from the 0.25-quantile to the 0.75-quantile of deviation with the bold line showing the 0.5-quantile of deviations. Whiskers show the 1.5-fold interquartile range and points indicate individual outliers.

Changes in crop yields

Decreasing crop yields

Future crop yields averaged over all locations contained in the household survey (Figure 3-3) decrease between 6 % and 24 % because of climate change depending on the GCM and management scenario (Table 3-5). The decrease is always weakest in the management scenarios with traditional sequential cropping systems. There are differences in mean crop yields and crop yield changes between the three GCMs, with the highest crop yields under CCSM3 and the lowest under ECHAM5. Southern and Western Africa are the most heavily impacted regions with declines in crop yield of up to 45 % and 18 % respectively depending on the management scenario (Figure 3-5). However, impacts in Southern Africa are diverse and crop yields in some locations also increase by up to 6 % in the TS scenario.

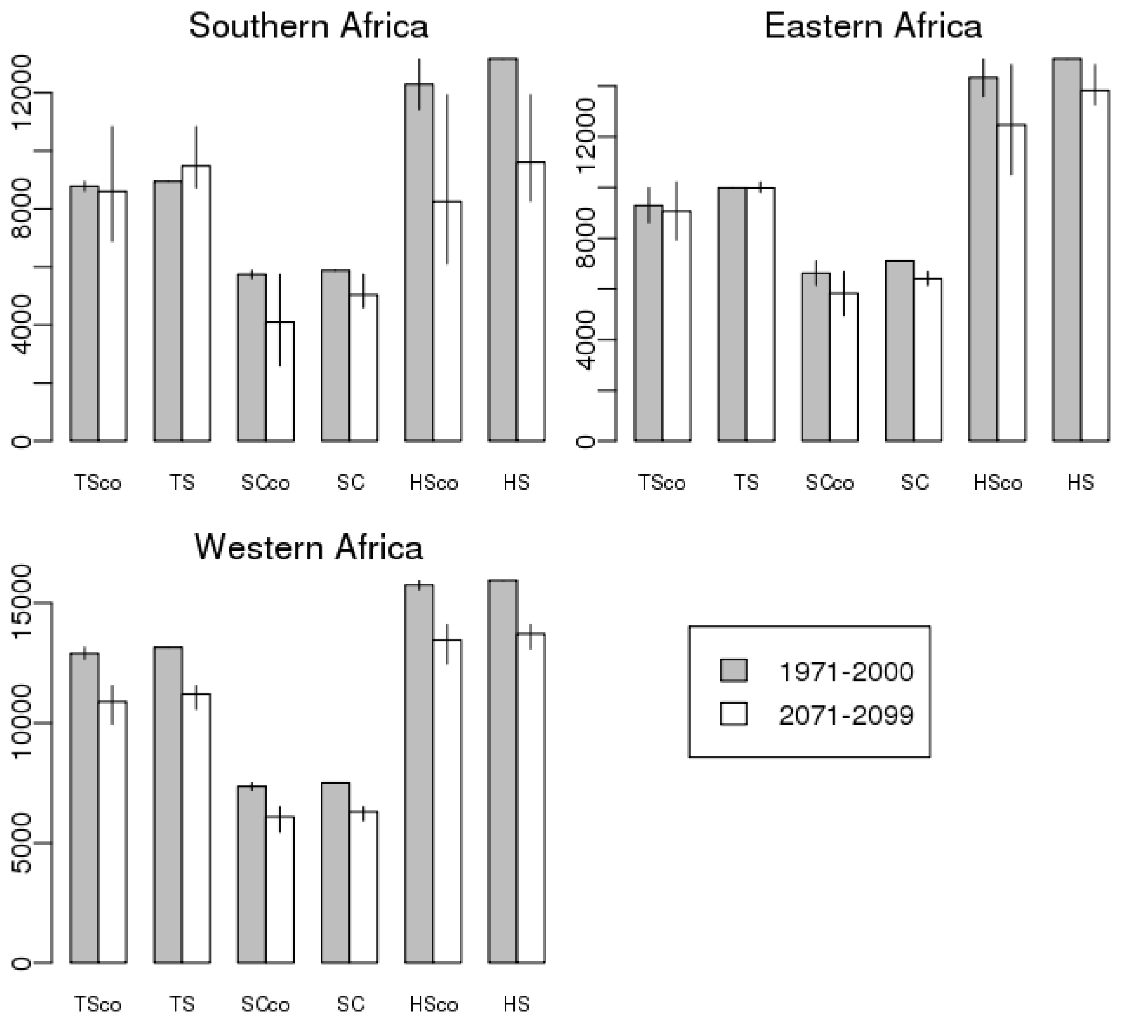

Figure 3-5 Mean crop yields [Mcal/ha] per region in 1971-2000 and in 2070-2099 if TS/TSco (the traditional sequence cropping systems), SC/SCco (only the first crop of the traditional sequential cropping systems), or HS/HSco (the highest-yielding sequential cropping systems) are applied, “co” indicates management scenarios with constant sowing dates (as computed for the first simulation year 1971). Vertical lines show the range of minimum to maximum crop yield from three GCMs. The countries of Zimbabwe and South Africa are combined into the region Southern Africa, Kenya and Ethiopia are combined into Eastern Africa and Burkina Faso, Cameroon and Ghana are combined into Western Africa.

Some traditional sequential cropping systems based on rice in Burkina Faso and based on groundnut in Ghana and Cameroon are most heavily impacted, with crop yield declines by at least 25 % (Table F-1 in Appendix F). In contrast, some traditional sequential cropping systems based on maize and wheat in Kenya and South Africa gain by at least 25 %. Mean future crop yields are higher (+ 11-17 %) in the TS, SC and HS scenarios with adapted sowing dates compared to the corresponding TSco, SCco and HSco scenarios with constant sowing dates (Table 3-5). As an exception, crop productivity in some single and sequential cropping systems in management scenarios with constant sowing dates is higher than in scenarios with adapted sowing dates (Table F-1).

Table 3-5 Mean crop yields and crop yield changes per GCM and management scenario in 63 districts of seven sub-Saharan Africa countries in the period 2070-2099 compared to the period 1971-2000 in six management scenarios.

	Crop yield 1971-2000 [Mcal/ha]	**Crop yield 2070-2099 [Mcal/ha]**		
Management Scenario	ECHAM5, HadCM3, CCSM3	ECHAM5	HadCM3	CCSM3
SCco	6660	5041 (-24%)	5459 (-18%)	5669 (-15%)
SC	7203	5894 (-18%)	6399 (-11%)	6393 (-11%)
TSco	10748	8942 (-17%)	9427 (-12%)	9799 (-9%)
TS	11564	10132 (-12%)	10677 (-8%)	10927 (-6%)
HSco	14435	11180 (-23%)	11676 (-19%)	12688 (-12%)
HS	15368	12796 (-17%)	13266 (-14%)	14095 (-8%)

TS/TSco: Traditional sequential cropping system, SC/SCco: Single cropping system, HS/HSco: Highest-yielding sequential cropping system, “co” indicating management scenarios with constant sowing dates

Sequential cropping systems vs. single cropping systems

Crop calorific yields in management scenarios with single cropping systems (SC/SCco) only reach 45 to 55 % of crop calorific yields obtained in management scenarios with sequential cropping systems (TS/TSco and HS/HSco) averaged over all locations contained in the household survey (Table 3-5). As an exception, the single cropping systems (SC/SCco) with maize in Kenya and South Africa yield higher in some locations than the traditional sequential cropping system, but only under current climatic conditions (Table F-1).

Crop yields in the highest-yielding sequential cropping systems (HS) exceed crop yields in the traditional sequential cropping systems (TS) by 24 to 28 % depending on the GCM (Table 3-5). However, frequently the traditional sequential cropping systems are more resilient against negative climate change impacts than the highest-yielding sequential cropping systems like e.g. groundnut-cassava systems in Cameroon, maize-maize systems in some locations in Kenya, wheat-maize systems in some locations in South Africa and maize-wheat systems in Zimbabwe (Table F-1).

Potential of sequential cropping systems in sub-Saharan Africa

If only the most stable sequential cropping systems would be chosen everywhere in sub-Saharan Africa, crop yields would be also less impacted by climate change than crop yields in single cropping systems in many locations (Figure 3-6). Crop yields in both systems mostly decline, most severely in western Mali, southern Mauritania and Senegal, but increase in small parts of South Africa, Kenya and Ethiopia. However, in the last-mentioned locations there is also the highest variability of climate change impacts on crop yields. The single cropping systems least impacted by climate change are cassava and maize, and to a smaller extent also rice. The sequential cropping systems least impacted are groundnut-cassava, rice-maize systems, but also maize-maize and maize-groundnut.

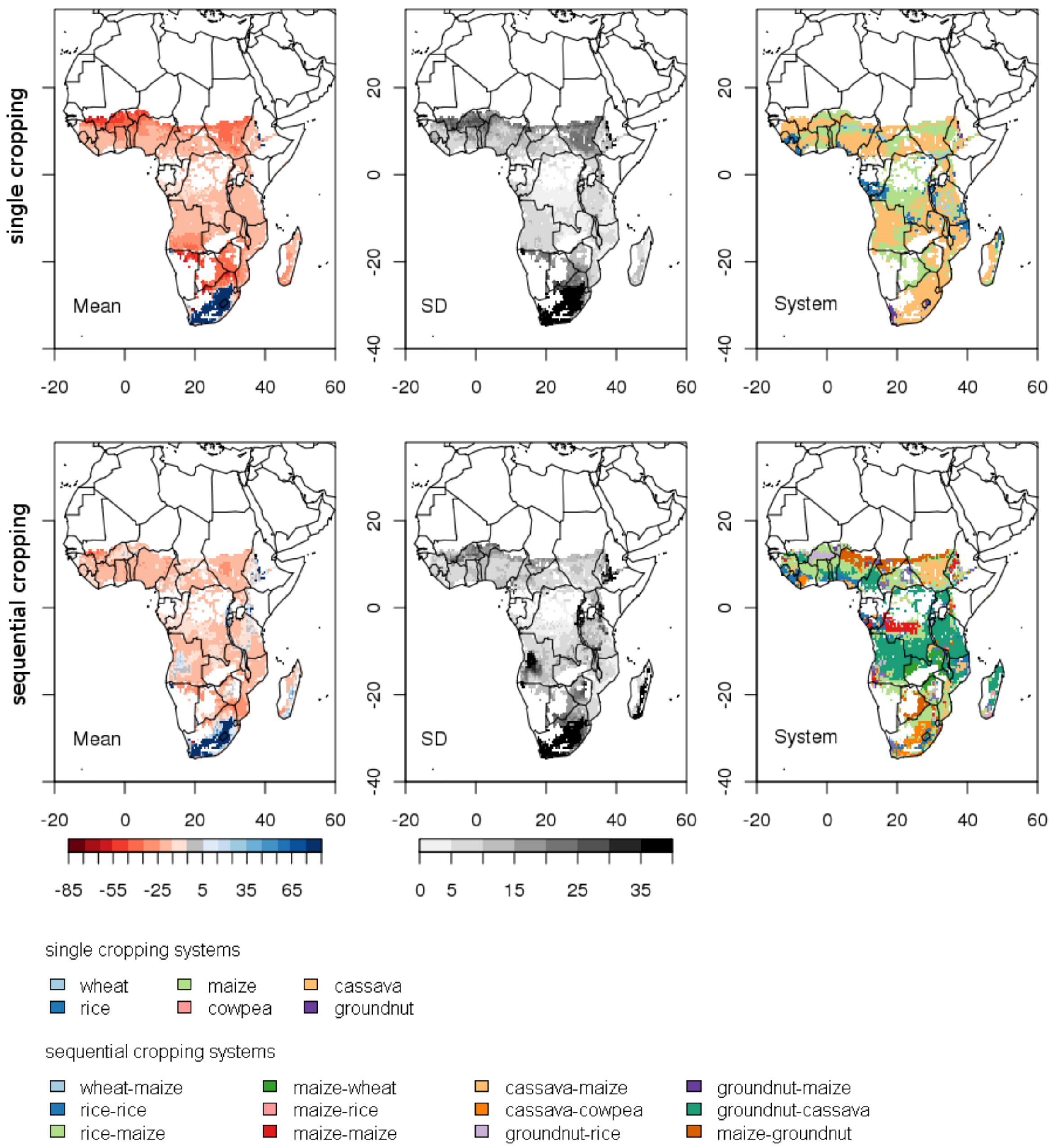

Figure 3-6 Mean crop yield changes (%) in 2070-2099 compared to 1971-2000 with corresponding standard deviations (%) in six single cropping systems (upper panel) and 13 sequential cropping systems (lower panel). Maps in the last column show the systems with lowest crop yield declines or highest crop yields increases. White areas in sub-Saharan Africa are excluded because the crop area is smaller than 0.001 % of the grid cell area or the growing season length is less than five months. The high standard deviation in Southern Africa is mainly determined by the large difference in climate projections.

3.4. DISCUSSION

Changes in crop yield

Crop yield decreases, mostly for single cropping systems, were also reported by other studies (Jones & Thornton, 2003; Lobell *et al.*, 2008; Schlenker & Lobell, 2010; Thornton *et al.*, 2011). Lobell *et al.* (2008) show declines in crop yield by up to 30% for maize in Southern Africa, millet in Central Africa and cowpea in Eastern Africa as early as 2030. In contrast to our results, Thornton *et al.* (2011) report higher mean production decreases for maize in 2090 in Western Africa than in Southern Africa, but in line with our results they project higher declines than in Eastern Africa. However, a comparison between these results and our study is difficult due to different time horizons, methodological approaches, climate projections and crop parameterization.

Mean crop yield decreases on average are most severe in Western and Southern Africa due to climate change (Table 3-6). Increasing annual temperatures in all regions lead to an accelerated phenological development and thus reduce growing periods by 31 to 65 days. Furthermore, growing season precipitation decreases in Southern Africa indicating a higher risk of water stress, in contrast to Eastern Africa with considerable increases in growing season precipitation. Water stress during the growing period affects photosynthesis as well as leaf and root growth, depending on the phenological stage (Figure C-1 in Appendix C). Therefore, total biomass as well as the biomass of harvested crop organs is reduced, depending on the crop type and cropping system. In contrast, in the temperate zone of South-East Africa precipitation is projected to increase or to remain constant from all three GCMs, leading to increased crop yields in some traditional sequential cropping systems (Figure 3-5) and also in some single cropping systems (Table F-1).

Table 3-6 Change in climate and length of the crops´ growing period in the period 2070-2099 compared to the period 1971-2000 in six management scenarios using climate projections from three GCMs.

	Southern Africa	Eastern Africa	Western Africa
ECHAM5			
Change in annual temperature [°C]	4,1	3,8	3,8
Change in annual precipitation [%]	-4,9	+11,4	+12,0
Change in growing season precipitation [%] [a]	-3,3	+11,4	+4,0
Change in length of crops´ growing period [b]	-65 days (-23%)	-35 days (-14%)	-36 days (-18%)
HadCM3			
Change in annual temperature [°C]	4,4	3,6	3,8
Change in annual precipitation [%]	-7,0	+9,7	-0,4
Change in growing season precipitation [%] [a]	-6,2	+12,8	+0,4
Change in length of crops´ growing period [b]	-60 days (-22%)	-31 days (-12%)	-36 days (-18%)
CCSM3			
Change in annual temperature [°C]	3,6	3,1	3,3
Change in annual precipitation [%]	+11,1	+24,8	+6,8
Change in growing season precipitation [%] [a]	+11,0	+24,7	+0,5
Change in length of crops´ growing period [b]	-43 days (-15%)	-29 days (-12%)	-31 days (-15%)

[a] growing season as indicated from satellite data providing the time of greening-up and greening down (HarvestChoice, 2010)

[b] growing period as simulated from LPJmL for different crops in six management scenarios

Farmers can lower the negative impact of changing climate on crop yields by adapting the sowing date to the start of the main rainy season, which is already done in many locations today. Simulation studies in Cameroon indicated that crop yields of maize and groundnut under climate change with an optimal planting date are higher compared to crop yields obtained using traditional planting dates, except for groundnut at one location (Laux *et al.*, 2010; Tingem & Rivington, 2009). This is in agreement with our findings, as the adaptation of sowing dates in our study usually results in higher crop productivity in these locations (Table 3-7). The benefits from adapted sowing dates are even higher in the literature, as both studies optimize the sowing date in order to maximize crop yields whereas in this study the sowing date is adapted to a shifted start of the rainy season.

Table 3-7 Comparison of simulated crop yields from literature and this study.

Location[a], crop	**Reference**	**Change to baseline, without adaptation**	**Change to baseline, with adaptation**	**Deviation between yield without and with adaptation**
Tiko/Moungo, groundnut	Tingem & Rivington (2009)	-5.1 %	+28.9 %	-
	this study	-25-29 %	-22-21 %	-
Ngaoundere/Vina, maize	Laux *et al.* (2010)	-	-	+1%
	this study	-19 %	-14-15%	+10.4-12.3%
Bamenda/Mbam and Bui, maize	Laux *et al.* (2010)	-	-	+16 %
	this study	-11-12 %	-12 %	-1.8- +2.9 %
Bamenda/Mbam and Bui, groundnut	Laux *et al.* (2010)	-	-	-9 %
	this study	-38 %	-32 %	+9.2 %

[a] locations in literature studies or related district in this study, e.g. the neighbouring district(s)

Attention should be paid to the different GCMs used in the studies in the literature and in this study. Crop yields from literature are shown for only one GCM (GISS), whereas in this study the results from three different GCMs are averaged. The SRES scenario and time horizon is identical.

With few exceptions, mean crop yields in sequential cropping systems exceed mean crop yields in single cropping systems because the second harvest will often also be successful under changing climatic conditions. The most productive sequential cropping systems are not always the most stable systems against negative climate change impacts. Instead the traditional sequential cropping systems which are already applied today will provide lower but more stable crop yields in many locations and poor farmers which rely on stable crop production will prefer them to highest-yielding cropping systems.

Limitations of the modeling approach

LPJmL is a vegetation model for managed land designed and parameterized for global or regional studies driven by aggregate soil and climate information. Detailed local soil and climatic conditions, specific agronomic practices, the occurrence of pests and diseases, various socio-economic aspects - despite their importance for local crop yields and farmers management decisions - therefore cannot be considered. Crop growth in advanced development stages is not terminated in the model by severe heat stress or desiccation. Crop yields are expected to decline by more than 10 % per °C temperature increase considering the effect of heat damage on maize grown in areas with growing season temperatures of more than 25 °C (Lobell *et al.*, 2011). However, temperature and water stress negatively affect photosynthesis, leaf and root growth and the production of storage organs during the growing period in the model and crop growth is terminated under poor growing conditions at the beginning of the phenological development. Therefore resowing within the same month is possible. The crop's influence on soil properties is not considered in the model but can noticeably benefit the yield of the subsequent crop by e.g. leaving nitrogen in the soil if cowpea is grown (Madamba *et al.*, 2006) or by improving the P-uptake of subsequent maize through mycorrhizal associations (Adjei-Nsiah, 2007) if cassava is grown. Furthermore crop rotations can reduce disease pressure from soil-or root-borne pathogens and pests and weed densities (Bennett *et al.*, 2012), which is not considered in our study.

As the cultivated area of each cropping system within the study area is still unknown, it remains unclear how the total crop production will be affected by climate change in each country if sequential cropping systems are considered.

Furthermore, developments in the demand for certain agricultural products, population size and availability of land and water resources must be considered when deciding on the most suitable management strategy for a location. The positive effects of elevated atmospheric CO_2 concentrations and technology development on crop yields are not considered in this study. Crop yields are expected to increase by 10-20 % for C_3 crops (e.g. wheat, rice) and 0-10 % for C_4 crops (e.g. maize, millet) if atmospheric CO_2 concentrations rise from 380 ppm to 550-600 ppm (Tubiello, 2007), but only if other biotic (like pests) or abiotic (like nutrients) factors do not become limiting (Long *et al.*, 2006). It is therefore unlikely that CO_2 fertilization will have a strong effect on crop yields at current management intensities in sub-Saharan Africa. If effective to some extend, the CO_2 fertilization effect will potentially reduce the superiority of maize-based systems, with maize being a less affected C_4 crop.

Uncertainties from the household survey

Although the questionnaire used in the household survey only asked for crops cultivated within one farming season, the length of the growing periods calculated for single and sequential cropping systems indicates that farmers also reported agricultural activities beyond that period. Despite excluding some obvious cases from the study it remains unclear if the reported farming activities refer to only one farming season in all cases. Moreover, crop failure was not reported in the survey, leading to uncertainty about the validity of the reported sowing and harvest dates in cases where farmers were forced to resow the chosen crop but did not report the new sowing date. In addition some crops, such as cassava, maize or legumes, might have an extended harvest period because of uneven ripening, better in-ground than out-of-ground storability or because multiple harvest products can be obtained from one crop (green and dry maize) (Fermont & Benson, 2011). This might lead to longer growing periods reported in the household survey than found in literature (Table 3-4). The geographic position of the households interviewed for the survey is not known, only the position of the districts they are located in. These were later used for the conversion from districts to grid cells. Therefore a considerable range of different cropping systems and growing periods can be found in a single grid cell, leading to some uncertainty in the multiple regression model between PHU_{sin} and the climate parameters which were used to describe the crop's development. However, the simulated lengths of growing periods differ only slightly between 5 and 33 days on average from those reported in the household survey, but with 50% of all values having a deviation of up to 58 and 65 days for cassava and groundnut respectively (Figure 3-4).

Farmers' adaptation options

Although sequential cropping systems are advantageous in terms of maximizing crop yields and minimizing climate change impacts compared to single cropping systems in many locations, farmers in 65% of the surveyed administrative units do not apply them. The growing season length in e.g. Senegal, Niger and parts of Ethiopia is not suitable to grow more than one crop. In districts climatically suitable for sequential cropping systems, growing a second crop requires sufficient labour and is risky if the rainy season ends too early and the crop fails. The first crop needs to be harvested, processed and stored or sold on the market during the period of land preparation and sowing of the second crop, which leads to a high demand for labour and possibly for draught animals (Gill, 1991). Moreover, introducing an unknown cropping system may also require some adjustments to current technology and management, which is often made more difficult by a lack of inputs like seeds or fertilizer, missing knowledge about cultivation and processing of the new cropping system and lacking market access to sell the products (Lotze-Campen & Schellnhuber, 2009). It therefore remains unclear if farmers will be able to apply the most beneficial cropping system.

Farmers will not only decide on the crop and cropping system with respect to productivity but also pay attention to other crop characteristics, such as its performance on local soils, the colour, shape and taste of harvestable organs, bacterial tolerance, market acceptability and storability (Haugerud & Collinson, 1990; Sperling *et al.*, 1993). In West Africa, farmers prefer e.g. an early-maturing millet cultivar at the beginning of the growing season because their food supply is very low after a long dry season and they need to harvest fast (Kowal & Kassam, 1978). In addition to adapting the cropping system and the crops' growing period to the best growing conditions, the farmers' options for adapting to changing climate include managing water resources by using e.g. water harvesting techniques (Kahinda *et al.*, 2007; Rost *et al.*, 2009), managing biodiversity, integrating animals into farming systems (Mortimore & Adams, 2001), diversifying livelihoods (Cooper *et al.*, 2008) and diversifying the whole agricultural system (Lin, 2011). We consider none of these options in our analysis here. In Tanzania, 33 different practices which are potentially suitable for adaptation to climate change, ranging from agricultural water management practices and adjustments of farm and crop management to diversification beyond the farm, are already used by farmers today (Below *et al.*, 2011). Indigenous soil conservation techniques and agro-forestry practices are additional examples for adaptation options not covered in this study. They are well known and already applied in local communities, as they conserve soil moisture and soil carbon (Nyong *et al.*, 2007) and protect crops from dry spells, extreme temperatures and storm events (Lin, 2011).

3.5. SUMMARY AND CONCLUSIONS

Farmers in sub-Saharan Africa grow a wide range of crops and apply different cropping systems, but as shown in our study clearly prefer long-growing crop cultivars in single cropping systems and short-growing crop cultivars in sequential cropping systems. For the first time, this study also shows the spatial distribution of sequential cropping systems applied in seven sub-Saharan Africa countries and enables us to analyse climate change effects on crop yields considering the cropping system type. They need to be included in climate change impact studies because simulated crop yields differ considerably between crops and cropping systems and also depend on the timing of sowing. Our newly developed modelling approach therefore helps to identify the best management strategy for adaptation to climate change. In single cropping systems crops grow longer but are only harvested once a year, leading to lower crop yields than in sequential cropping systems with shorter growing periods but higher cropping intensities. However, only farmers in regions with adequate temperature, precipitation and solar radiation can benefit from higher cropping intensities in sequential cropping systems. It is important to note that farmers are able to reduce the negative effects of climate change and minimize the risk of crop failure by applying low-tech adaptation options on a farm level. Despite the advantage of sequential cropping systems over single cropping systems in many locations since both higher crop yields and lower declines in crop yield in future are possible, farmers might not always be able to apply them if inputs and labour for agricultural production are lacking. This implies that farmers would benefit from improved knowledge and further field studies about crops and cropping systems, also ones currently uncommon in their country, and from reliable weather and seasonal climate forecasts. Furthermore, stable economic and political conditions would support private trading and the further development of market opportunities. Such conditions would strengthen the farmers' adaptive capacity, perhaps also allowing them to take advantage of sequential cropping systems while at the same time facing the challenge of changing climate conditions.

3.6. ACKNOWLEDGEMENTS

We would like to thank the LPJmL crop modeling team and especially Susanne Rolinski for valuable discussions on the methodology and results. Furthermore we are grateful to Benjamin Gaede and Alison Schlums, who checked the spelling and grammar. K.W. and C.M. gratefully acknowledge financial support from projects with the International Food Policy Research Institute (6012001) and the International Livestock Research Institute (81102850) funded through the German Federal Ministry for Economic Cooperation and Development. We are grateful to HarvestChoice for providing data on growing seasons in sub-Saharan Africa and rice yield in Somalia. The Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP's Working Group on Coupled Modelling (WGCM) are acknowledged for making available the WCRP CMIP3 multi-model dataset.

3.7. AUTHORS´ CONTRIBUTION

The contribution of the different authors was as follows: K.W. and C.M. conceived the original idea of studying the susceptibility of multiple cropping systems to climate change, K.W., C.M., A.B., J.P.D. and H.L.-C. were involved in developing the methodology. K.W., C.M., A.B. and J.H. implemented the concepts in the model, K.W. analysed the household survey supported by P.K. who provided the original database of the survey, K.W. did the model runs, prepared the figures, did literature research, wrote the manuscript and prepared the supporting material. All authors were involved in discussing the results.

4. Separating the effects of temperature and precipitation change on maize yields in sub-Saharan Africa

Our aim is to analyse the separated and combined effects of temperature increase and changing precipitation patterns on maize yields in sub-Saharan Africa. Under changing climate, both climate variables are projected to change severely, and their impacts on agricultural vegetation are frequently assessed using process-based crop models. However the extent to which different agroclimatic variables influence crop growth and development in these models is not clear. Analysing them separately helps (i) to identify the limiting effect on crop growth and yield in different environments and (ii) to understand the effects of increasing temperatures and changing precipitation patterns in a process-based crop model.

We analyse daily precipitation data as projected from nine global climate models and create synthetic climate scenarios from these to study the effect of large changes in the wet season precipitation and in the wet season length both separately and in combination with changes in temperature. The dynamic global vegetation model for managed land LPJmL (Bondeau *et al.*, 2007) is used to simulate maize yields under current and future climatic conditions for the two 10-years periods 2056-2065 and 2081-2090 for the A1b emission scenario and at constant atmospheric CO_2 concentrations of 370 ppm.

The importance of temperature and precipitation effects on maize yields varies spatially and we identify four groups of crop yield changes: regions which are very susceptible to climate change (< -33 %), regions which are moderately (-33 % to -10 %) or slightly susceptible (-10 % to +6 %) to climate change and regions which are not susceptible to climate change but benefit from increasing temperatures (> +6 %). Temperature increases lead to maize yield reductions of 3 to 20 %, with the exception of mountainous and thus cooler regions in South and East Africa. A reduction of the wet season precipitation causes decreases in maize yield of up to 30 % and more and prevails over the effect of increased temperatures in southern parts of Mozambique and Zambia, the Sahel and parts of Eastern Africa in the 2060s and the 2085s. In most regions maize yields are not reduced due to a shortened wet season, as the crop is simulated to start growing at the onset of the wet season. Only in small parts of the Sahel and southern Africa with short wet seasons not exceeding 100 days, maize yields are reduced if the wet season is shortened. This knowledge about the limiting abiotic stress factor in each region will help to prioritize future research needs in drought and heat stress breeding programmes and to identify adaption options in agricultural development projects.

This chapter is under review at *Global and Planetary Change* as: Waha, K., Müller, C., Rolinski, S., Separating the effects of temperature and precipitation on maize yields in sub-Saharan Africa.

4.1. INTRODUCTION

Global dynamic vegetation models are frequently used to simulate climate change impacts on agricultural crops in sub-Saharan Africa and many studies can be found in the literature for either the whole region (Folberth *et al.*, 2012; Jones & Thornton, 2003; Liu *et al.*, 2008; Thornton *et al.*, 2011) or for individual African countries (Adejuwon, 2006; Laux *et al.*, 2010; Thornton *et al.*, 2009). These models compute important biophysical and biochemical processes, like photosynthesis, respiration and transpiration or the dynamics of carbon and water at the leaf-level (Bondeau *et al.*, 2007; Tubiello & Ewert, 2002) and are therefore able to simulate the effect of increasing temperatures, changing precipitation and elevated atmospheric CO_2 concentrations on crop development and yields. Climate projections from general circulation models (GCMs) on monthly air temperatures, monthly precipitation and annual atmospheric CO_2 concentrations are used as input for these models. For sub-Saharan Africa GCM projections agree well in the level of a median temperature increase between 3 to 4°C, depending on the season and region in the 2090s compared to the 1990s in the A1b projections (Christensen *et al.*, 2007). The likelihood that the summer average temperature will exceed the highest summer temperature on record is greater than 90 % in West and East Africa in the 2050s and in nearly all parts of sub-Saharan Africa in the 2090s (Battisti & Naylor, 2009). GCM projections of annual precipitation changes in the 2090s compared to the 1990s in the A1b projections vary strongly between +13 to -9 % in Western Africa, +6 to -12 % in Southern Africa and +57 to -44 % in the Sahel region (Christensen *et al.*, 2007). Analysing an ensemble of nine GCM projections shows that the length of the growing season in the 2090s will be reduced by 5 to 20% in most parts of Africa and by more than 20% in the Sahel and Southern Africa (Thornton *et al.*, 2011), leading to an expansion of arid areas with a growing season length of less than 120 days by 5-8 % in the 2080s (Fischer *et al.*, 2002a). Additionally an increase in the number of extremely wet seasons in West Africa and East Africa by 20 % and an increase of extremely dry seasons by 20 % in southern Africa combined with an increase in the rainfall intensity is expected (Christensen *et al.*, 2007).

Temperature and precipitation changes might limit the plants` growth and development to a different extent depending on the current growing conditions and the magnitude of climate change. In the literature studies disagree about the importance of temperature and precipitation changes for crop yield changes and some studies focus on a single effect only. Increasing temperatures have strong effects on crops, e.g. maize yields in regions with an average growing season temperature above 25°C decline by more than 10 % per °C of warming as evidenced by field data (Lobell *et al.*, 2011). In a statistical analysis on country-level crop yields and climate data, Schlenker & Lobell (2010) show that impacts on aggregated crop yields in sub-Saharan Africa due to temperature changes are much stronger (-38 % to +12 %) than impacts due to precipitation changes (-3 % to +3 %) for five different crops. Consequently they doubt that shifts in the distribution of growing season rainfall will outweigh temperature effects on yield. In contrast, studies on rainfall variability and crop yields highlight the importance of variable wet season starts and the occurrence of dry spells for crop yields (Barron *et al.*, 2003; Sultan *et al.*, 2005). Dry spells in the flowering phase at two semi-arid locations in East Africa are estimated to reduce potential maize yields by 15-75 % depending on soil water-holding capacity (Barron *et al.*, 2003). Long periods of droughts in low-rainfall years have also seriously affected Africa's agriculture and economy in the past (Sivakumar *et al.*, 2005) and will remain a danger in water-limited environments. Finally, in a survey on crop modeling, food security and climate change scientists stated that in studies on climate variability there is indication that precipitation variation has the greatest influence on crop yields (Rivington & Koo, 2011). With climate change, both temperatures and precipitation will change and a combination of drought and heat stress will have an even more significant effect on crops than each effect separately (Barnabas *et al.*, 2008).

Analysing the effects of precipitation and temperature changes separately and in combination is important for understanding and modeling climate change impacts on agriculture. It helps identifying the constraining factors for agricultural production in different environments and prioritizing adaptation strategies to climate change. The success of breeding programs and farmers in selecting drought- or heat-tolerant crop cultivars will be depending on the knowledge about changing growing conditions and the severity of different types of abiotic stresses. This paper analyses the separated and combined effect of changes in the temperature, wet season length and wet season precipitation on crop productivity. We generate synthetic climate data for each grid cell by adding projected changes in the wet season length and the wet season precipitation to observed daily time series. As this causes variations in the mean daily precipitation, the total wet season precipitation and the number of small and large precipitation events, we are also able to analyse effects of changing precipitation variability on crop yields. This climate data is used as input for the global dynamic vegetation model LPJmL (Bondeau *et al.*, 2007; Gerten *et al.*, 2004). The model is able to simulate crop yields of the major food crops in Africa (Appendix E in Chapter 3). We choose maize as an example crop as it is the most important food crop in sub-Saharan Africa. We aim firstly at describing the individual importance of temperature increases and changing precipitation patterns for maize yields in different regions of sub-Saharan Africa in order to identify the limiting effect for maize growth. In this context we aim at enhancing the understanding of temperature and water stress effects in the model in order to identify future research and model development needs.

4.2. MATERIALS AND METHODS

Climate data

Projections on daily precipitation, monthly mean air temperatures and monthly cloudiness for two time periods were taken from nine GCMs for the A1b emission scenario from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset (Meehl *et al.*, 2007). We choose these GCMs with available and complete data on daily precipitation, air temperature and cloudiness (Appendix G). The future climate in the two time periods is represented by climate data in 2056-2065, 2060s hereafter, and in 2081-2090, 2085s hereafter. The study area comprises all grid cells in Africa from 40° N to 40° S and from 20° W to 60° E.

Daily precipitation data for the baseline climate 1991-2000, 1995s hereafter, were taken from WATCH Forcing Data (WFD) (Weedon *et al.*, 2011). This data set combines monthly precipitation totals from the Global Precipitation Climatology Center (GPCCv4) (Fuchs, 2009; Rudolf & Schneider, 2005; Schneider *et al.*, 2008) and reanalysis data on day to day variability from the European Centre for Medium-

Range Weather Forecasts database (ERA - 40) (Dee *et al.*, 2011). Future daily precipitation is generated from GCM projections according to climate experiments described below in order to study the effect of changes in the wet season length and wet season precipitation.

Monthly temperature and cloudiness for the baseline climate 1991-2000 were taken from the Climate Research Unit database (CRU TS 3.0) (Mitchell & Jones, 2005). For future climates, monthly temperature and cloudiness anomalies from each GCM were calculated for each year and month relative to the year 2005 after interpolating data to a resolution of 0.5° x 0.5° and smoothing using a 30-year running mean. For temperatures, the anomalies were simply added and for cloudiness the relative changes were applied (for further details see Gerten *et al.*, 2011) to current monthly climate data fields constructed from CRU TS 3.0 1961-2005 data. Daily mean temperatures are obtained by linear interpolation between mean monthly temperatures. The atmospheric CO_2 concentrations are kept constant at a level of 370 ppm.

Climate experiments

Generating synthetic climate experiments from GCM projections allows analyzing the effects of changes in the wet season length and the wet season precipitation both separately and in combination with temperature changes in each grid cell. We are therefore able to test the sensitivity of the crop model to each agroclimatic variable separately.

In a first step, we calculate the relative change of the wet season length and precipitation in the 2060s and in the 2085s compared to the 1995s for each grid cell from daily precipitation data of nine GCMs. The onset of the wet season is defined following Dodd & Jolliffe (2001) as a period of six consecutive days with at least 25 mm rainfall in which the start day and at least two other days are wet and no dry period of ten or more days occurs in the following 40 days. Accordingly, the wet season ends if there is no precipitation for ten consecutive days. In a second step we identify the GCM projecting the largest relative change in the length and total precipitation of the wet season for each grid cell after removing the outliers that deviate from the mean by more than two standard deviations to avoid extreme changes (see Appendix H). This procedure leads to rather negative precipitation projections for each grid cell, neglecting the large range of precipitation projections among the GCMs, but ensuring a reasonable level of changes in accordance with at least one GCM. These changes in wet season characteristics are applied to the daily precipitation series of the baseline climate (Figure 4-1) both separately and in combination with temperature changes studying the effect of:

- **c**hanges in the wet season **p**recipitation only (Cp),
- **c**hanges in the **l**ength of the wet season only (Cl),
- **c**hanges in the monthly mean **t**emperatures only (Ct), and
- changes in all three agroclimatic variables (CpClCt).

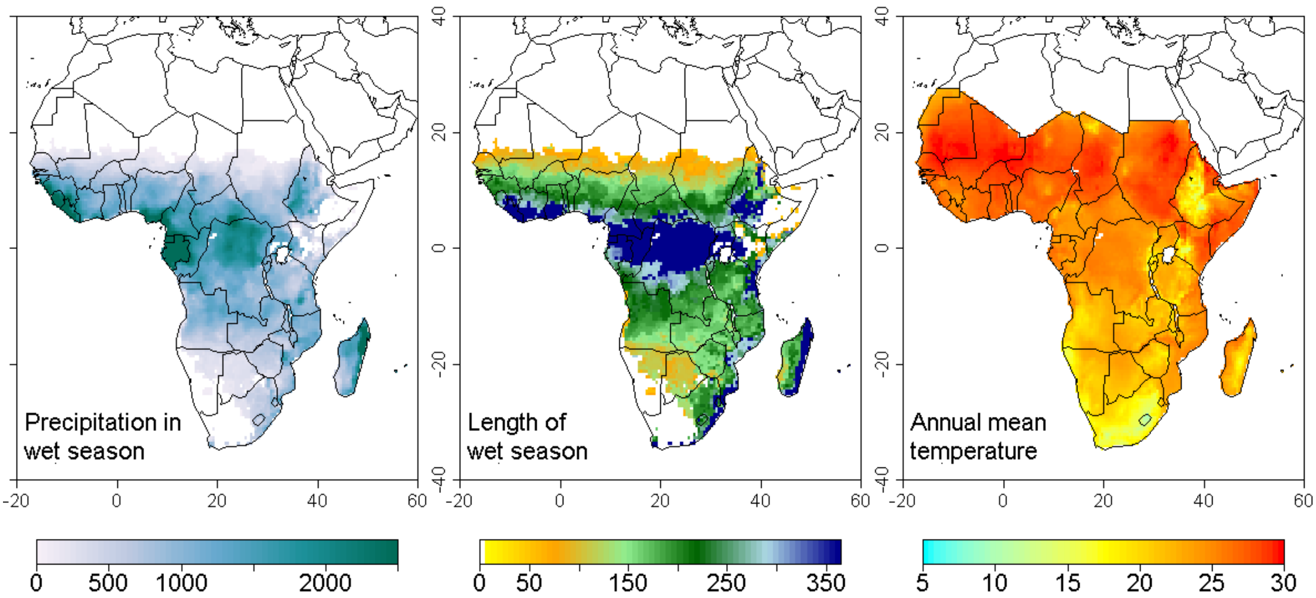

Figure 4-1 Precipitation in the wet season (mm), length of the wet season (days) and annual mean temperature (°C) in the 1995s as calculated from daily precipitation and monthly temperatures. White colors indicate regions with a bimodal rainfall regime (Eastern Africa) or desert areas (Southern Africa) where no main wet season could be identified.

If the length of the wet season decreases, experiment Cl is realized by distributing the precipitation sum of the removed days equally to the remaining rain days in order to avoid altering the precipitation amount in the wet season. Consequently, the number of rain days decreases and the mean rainfall per rain day as well as the risk of extreme rainfall events increases. In contrast, mean rainfall per rain day decreases in experiment Cp, which reduces the risk of extreme rainfall events. The mean rainfall per rain day in experiment CpClCt depends on the magnitude of both changes and on the precipitation amounts at the end of the wet season. The length of dry spells within the (shortened) wet season is not changed in any of these experiments, only the number of rain days and the number of small and large precipitation events (Figure H-1 in Appendix H).

For the two future time periods in experiments Cp and Cl, monthly mean temperatures and cloudiness are kept constant over time with the baseline climate and are changing according to GCM projections in experiments Ct and CpClCt. Temperature and cloudiness data were chosen in each grid cell from the GCM that was selected for precipitation projections in this grid cell. In total four climate experiments (three experiments for separated effects, one for combined effect) per grid cell are conducted.

Modelling the impact on agricultural vegetation

The impact of changing precipitation patterns in combination with an increasing mean annual temperature on agricultural vegetation in sub-Saharan Africa can be simulated with the global dynamic vegetation model LPJmL (Bondeau *et al.*, 2007; Gerten *et al.*, 2004; Sitch *et al.*, 2003). LPJmL is designed to simulate biophysical and biogeochemical processes as well as productivity and yield of the most important crops at daily time steps on global scale. Water stress influences leaf growth (Bondeau *et al.*, 2007) and root growth (Appendix C), which both affect the amount of harvestable biomass. Modifications of leaf and root growth are based on a water stress factor (WSF [0,1]) calculated for each day and accumulated for all days with water stress for root growth. WSF is calculated from the ratio of daily water supply, i.e. plant water uptake from the soil, and daily atmospheric water demand, i.e. potential evapotranspiration (Sitch *et al.*, 2003). High temperatures below or above crop-specific optimal temperatures for photosynthesis (21-26 °C for maize) reduce the photosynthesis rate (Haxeltine & Prentice, 1996), and increasing temperatures accelerate plant development and therefore lead to lower grain yields.

The start of the growing period in all time steps is determined by the start of the rainy season from daily precipitation in the 1995s as described above (subsection "Climate experiments”). The length of the growing period is represented individually for each crop by the phenological heat units (PHUs) required to reach maturity. They are calculated from a multiple linear regression model between PHUs and climatic variables in each grid cell (Chapter 3.2) for each crop separately. For maize this relationship is rather weak but PHUs are in a reasonable range between 1880°Cd and 3640°Cd (Table 3-2 in Chapter 3). Sowing dates and PHUs for maize are calculated once for climate conditions in the baseline climate and are kept constant over time. We do not allow for adaptation of sowing dates or crop cultivar in order to clearly separate the climate effects from possible adaptation measures. For the same reason only rainfed, single cropping systems are simulated as irrigation or growing a second crop if the growing season is long enough would influence crop yields considerably. The management intensity in a grid cell influences the attainable crop yield and is described by three parameters: the maximal attainable leaf area index, the maximal harvest index and a parameter scaling leaf-level biomass to field level as described in Fader *et al.* (2010). The management intensities per country were chosen to match observed production levels of FAO in the 5-years period 1999-2003.

For this study, maize yields were calculated by running LPJmL with the four climate experiments described above. The change in yield for each grid cell and the two time periods (2060s and 2085s) is calculated as a result of changes in mean annual temperature only (ΔYI_{Ct}), wet season precipitation only (ΔYI_{Cp}), wet season length only (ΔYI_{Cl}) and in all three agroclimatic variables (ΔYI_{CpClCt}) (see Appendix I). The methodology and expected results are summarized in Figure 4-2.

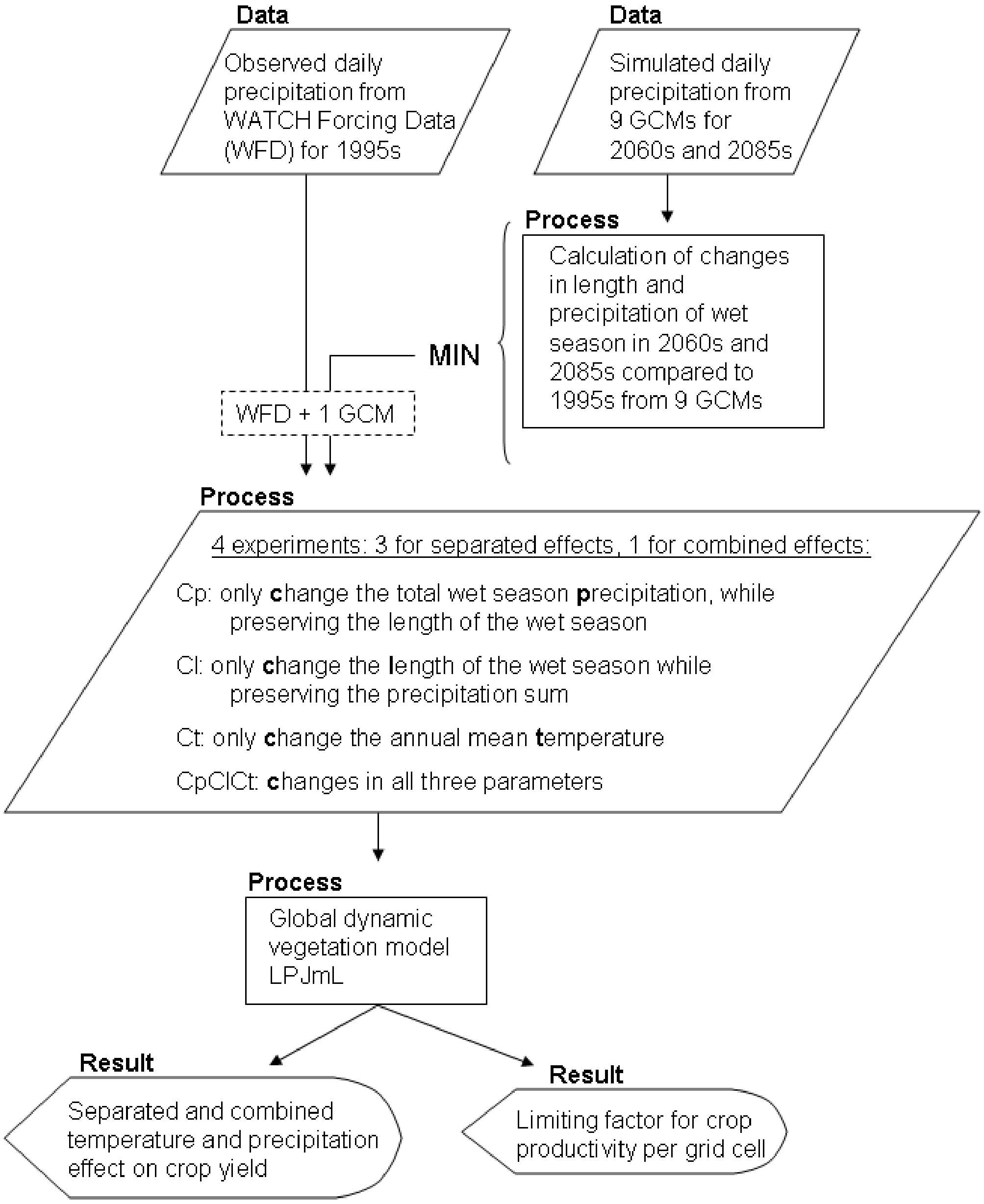

Figure 4-2 Graphical abstract of data, methods and expected results in this study.

4.3. RESULTS

We focus on results for grid cells with unimodal rainfall distributions, and at least 0.001% of the grid cell area covered with maize. We show changes in mean annual temperature, wet season length and precipitation used as input data for the global dynamic vegetation model and impacts of these changes on maize yield in the 2060s and the 2085s.

Changes in temperature, wet season length and precipitation amount

GCM-projected daily precipitation data was analysed with regard to the largest changes in the wet season precipitation and wet season length per grid cell after removing the outliers. Note that these are stylized climate experiments combining changes from different GCMs and using them as input for the global crop model. The GCMs GFDL-CM2.1, GFDL-CM2.0 and CNRM-CM3 project the largest changes in the wet season length and precipitation in many parts of SSA, therefore the stylized climate experiments in almost half of the grid cells are based on climate change projections from one of these models. In the second half climate data from the remaining six GCMs is used in equal parts as input for the crop model. Most parts of sub-Saharan Africa experience decreases in both variables of up to 20 % (Figure 4-3). The wet season length and precipitation decrease most severely in parts of the Sahel, Southern Africa and Central Africa. The spatial patterns of changes in precipitation amount and length of the wet season are very similar in most parts. However, in some regions the precipitation amount in the wet season decreases more than the length of the wet season, like e.g. in West and East Africa between 5 °N and 18 °N. In contrast, the length of the wet season decreases more than the wet season precipitation in parts of Tanzania, northern Mozambique, Ethiopia or Angola. The wet season length and precipitation increase in 1.9-5.9 % of all grid cells depending on the time period. Annual mean temperatures increase by 2-3 K in the 2060s and by 4-5 K in the 2085s whereas the increase is strongest in southern Africa and in the Sahel (Figure 4-3).

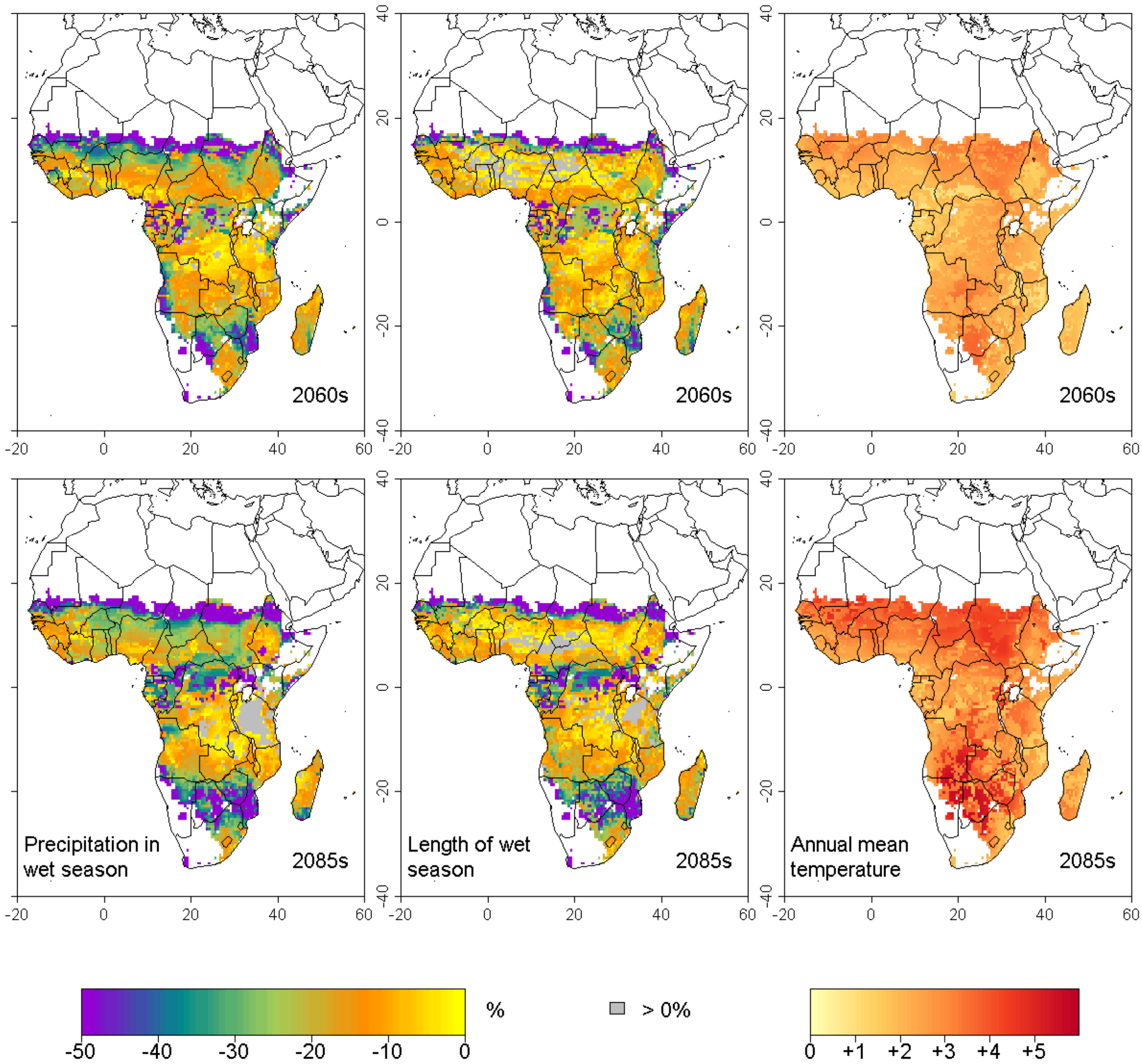

Figure 4-3 Change in important agroclimatic variables according to GCM projections in the 2060s (top) and 2085s (bottom) compared to the 1995s (from left to right): wet season precipitation, wet season length and annual mean temperature. The largest changes in the wet season per grid cell after removing the outliers and the corresponding temperatures are shown. Dark violet colors in the leftmost and middle panel indicate a reduction of 50 % or more.

Impacts on agricultural vegetation in sub-Saharan Africa

We compare simulations with the global dynamic vegetation model LPJmL driven by the four climate experiments described in the methodology section in order to estimate the impact of changes in wet season characteristics and in temperatures, attributing the effects on crop productivity to these individual drivers.

Temperature increases lead to crop yield reductions in the 2060s in the maize-growing regions of sub-Saharan Africa of 3-20 %, except for mountainous regions in South and East Africa and parts of western Africa (Figure 4-4). In most regions maize yields are lower in the 2085s than in the 2060s. The effect of reduced precipitation on maize yields is even stronger in Southern Africa, southern parts of Mozambique and Zambia, the Sahel and parts of Eastern Africa, with yield reductions of up to 30 % and more. The effect of reduced precipitation in these regions clearly prevails over the effect of increased temperatures in the 2060s and the 2085s. In all other parts, e.g. in Central and Western Africa south of 13° N, the effect of increasing temperature is limiting because of very slight yield changes due to changes in wet season precipitation of -3 % to +3 %. In the mountainous regions of eastern and southern Africa, increasing temperature leads to increasing crop productivity of up to 30 % and more, making reduced precipitation the only limiting effect. The reductions in maize yields of 30 % and more in southern Africa result from very different precipitation decreases of 50 % and more in southern Mozambique and Zimbabwe, but only 10-20 % in South Africa (Figure 4-3). A shortening of the rainy season does not affect maize yield negatively in most regions but partly leads to increasing crop yields. Maize yields in central Africa with an already long rainy season (>200 days) are not affected by a shortened wet season at all.

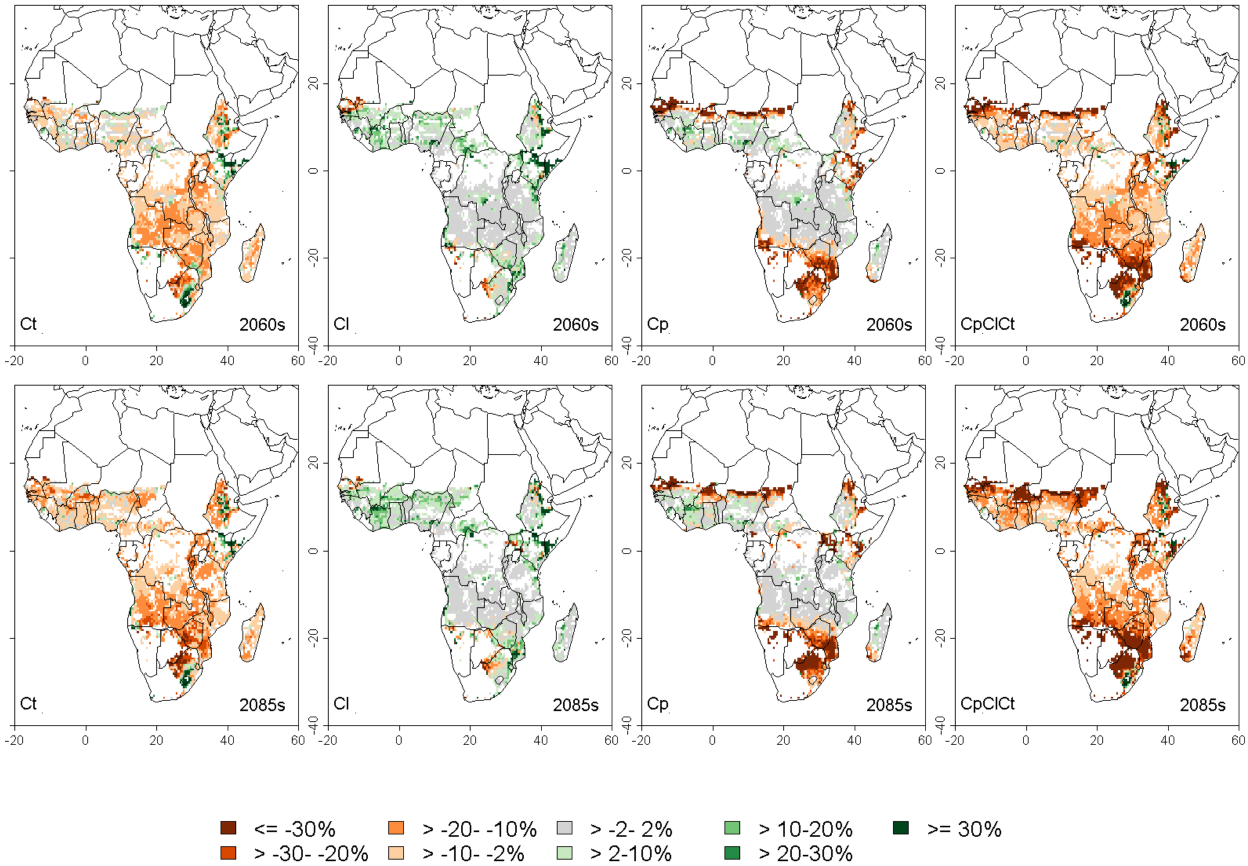

Figure 4-4 Changes in rainfed maize yield calculated with LPJmL in the 2060s (top) and 2085s (bottom), due to (from left to right) increasing annual mean temperature (Ct), shortened wet season (Cl), reduced wet season precipitation (Cp), and the combined effect from all three (CpClCt).

4.4. DISCUSSION

Aggregating and understanding crop yield changes

The crop yield changes presented in Figure 4-4 result from stylized climate experiments with rather large changes in the wet season precipitation and the wet season length and show the climate change effect on maize yields in each grid cell. They differ a lot between regions depending on the initial climate conditions determining the crop's growing conditions and the magnitude of climate change. It is possible, however to identify groups of grid cells with similar crop yield changes. We group the grid cells according to changes in maize yields due to the combined effects of temperature and precipitation changes (CpClCt) in the 2060s, applying hierarchical cluster analysis with the Ward's minimum variance method as a criterion for building clusters with the R function *hclust* (Murtagh, 1985). The distance between 1-dimensional clusters is calculated as the Euclidean distance. Each cluster differs in the future crop yield changes (Figure 4-6) which indicate a high or low susceptibility to climate change. The initial climatic conditions in the baseline climate in each cluster might be different among the clusters as well (Figure 4-5, right side), as final crop yields depend not only on the magnitude of climate change but also on the initial climate conditions determining the crop's growing conditions.

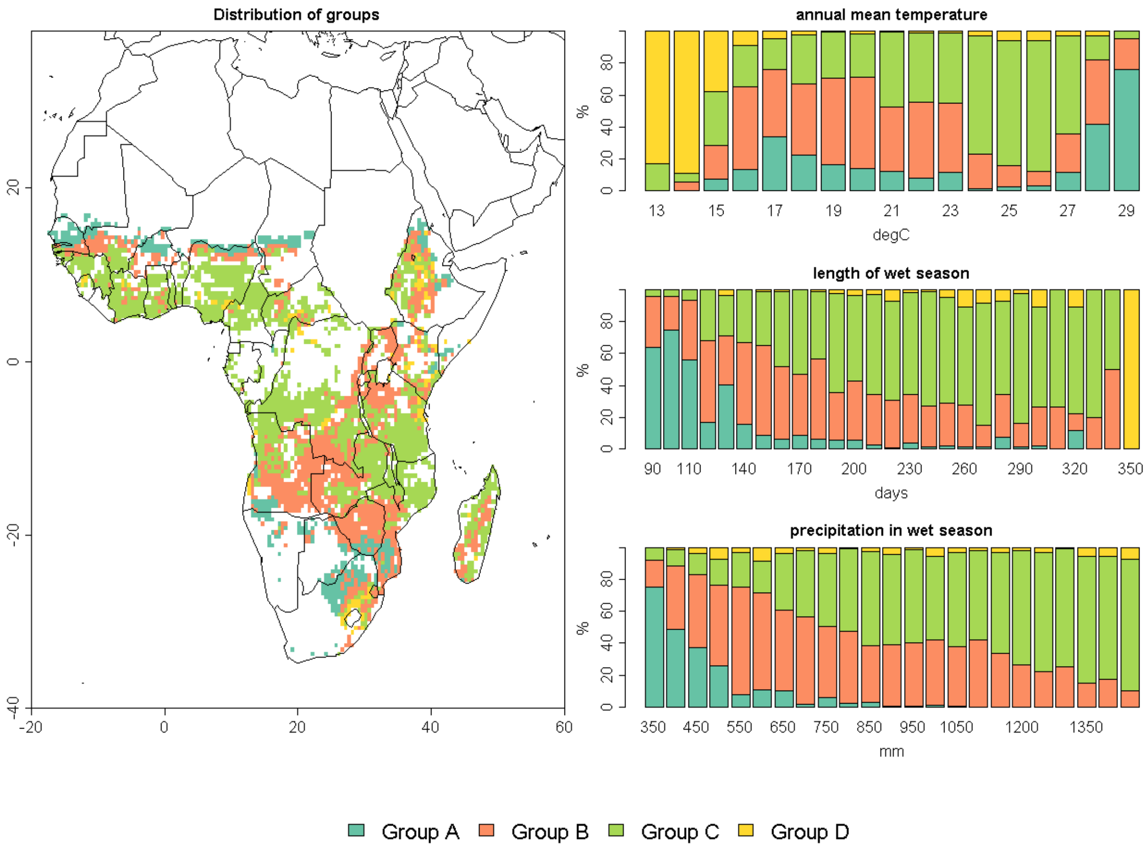

Figure 4-5 Distribution and characteristics of four groups resulting from hierarchical cluster analyses of yield changes in the 2060s (Figure 4-4, panel top right). The stacked bar plots on the right side show the probability that grid cells within a group belong to a certain temperature class, wet season length class and wet season precipitation class. Labels at the x-axis are the lower class limits.

Grid cells attributed to group A are located in the Sahel, in southern Africa and in parts of Eastern Africa. The group is very susceptible to climate change with large maize yield decreases of at least 33 % (Figure 4-6). Mean annual temperature in the baseline climate is mostly above 28 °C, the wet season length is below 120 days and the wet season precipitation is below 500 mm (Figure 4-5, right side). High mean annual temperatures in the baseline climate and temperature increases of 2-3 K until 2060 indicate an increasing risk of extreme daily temperatures in group A. However, according to our results a reduction in the wet season precipitation causes a stronger decrease in crop yields than increasing temperatures in nearly all grid cells assigned to this group (Figure 4-6). The growing conditions in this group are unfavourable for growing crops already today but temperatures far beyond the temperature optimum for photosynthesis (21-26 °C) do not damage the crop additionally in the model, leading to a weak temperature effect compared to the precipitation effect.

Group B and group C are moderately to slightly susceptible to climate change with maize yield changes between -33 % to -10 % and -10 % to +6 %, respectively (Figure 4-5). Parts of Western Africa south of 13° N and of Central and East Africa are belonging to group C, which is characterized by high annual mean temperature (24-28 °C) and sufficient amounts of precipitation in the wet season (>750 mm). In most grid cells belonging to group B or C the growing season is long and wet enough for growing maize in a single cropping system so the length of the wet season does not determine the magnitude of yield changes. For the same reason the effect of a reduced wet season precipitation is less strong than the effect of increasing temperatures (Figure 4-6). Temperatures increase are slightly stronger in parts of southern Africa belonging to group B (Figure 4-3) leading to a stronger temperature effect on maize yields than that in group C. A shorter wet season (CI) only has a marginal effect on maize yields in group B and C as the growing conditions are not necessarily affected if the crop reaches maturity before the end of the wet season.

Group D is the smallest group and not susceptible to climate change at all. Maize yield increases by at least 6 % (Figure 4-6) because increasing temperatures are favourable in an environment with an annual mean temperature between 13 °C and 15 °C and a long wet season (Figure 4-5, right side). As also the mean rainfall per rain day is increased in the CI experiment with a shortened wet season, the growing conditions improve leading to increasing maize yields in some regions i.e. many grid cells in group D.

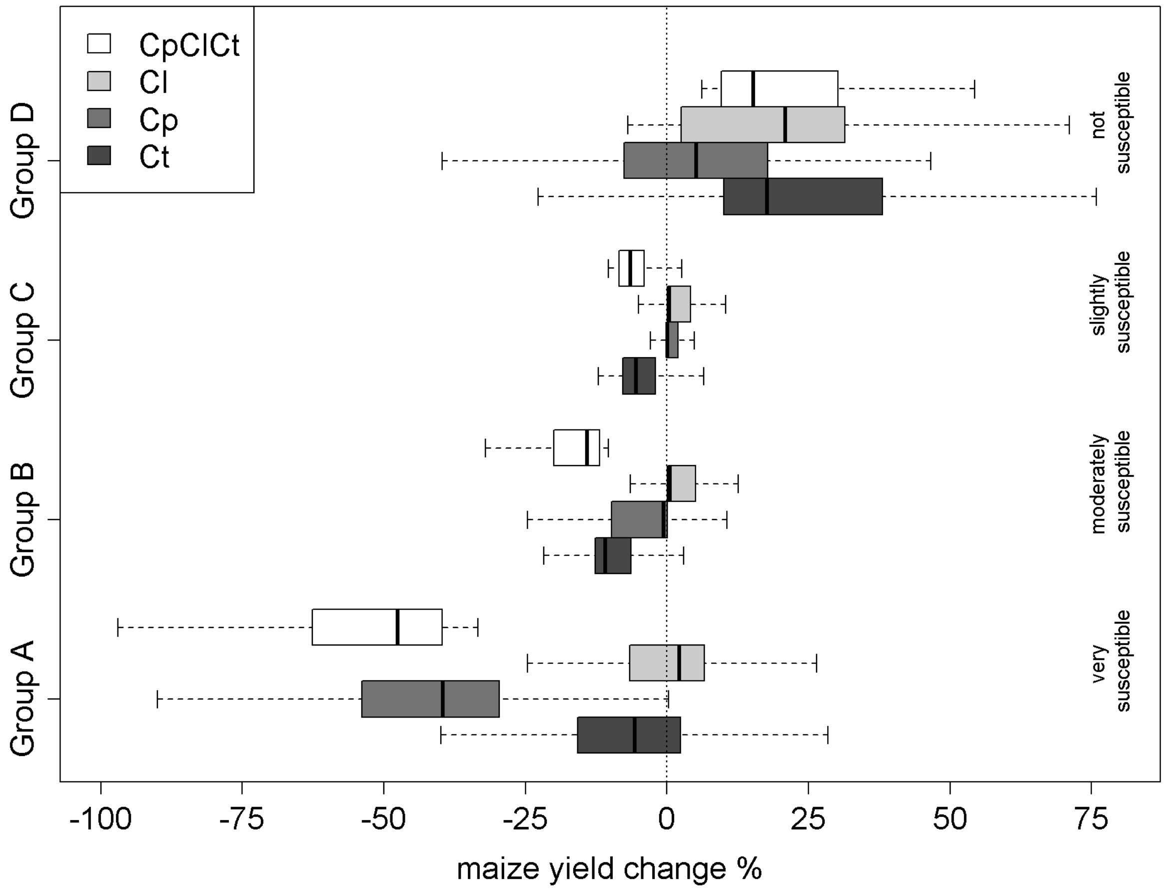

Figure 4-6 Crop yield changes in the 2060s from the combined (CpClCt) and separated effects of changing temperature (Ct) and wet seasons (Cp, Cl) in groups shown in Figure 4-5. Extreme data points that deviate from the borders of the box (Q25-Q75) by more than 1.5 times the interquartile range are not shown.

In group A-C with slight to large reductions in maize yields, the limiting effect in each grid cell also determines the direction of yield change if all three effects are combined and negative effects from increasing temperature and changing precipitation exacerbate each other (Figure 4-4 for e.g. Zimbabwe, southern Mali or Burkina Faso). In group D, in contrast the combined effect of changing temperatures and precipitation is positive following mostly from the beneficial effect of increasing temperatures.

Even slight to moderate yield changes might seriously endanger local food security if food production is already instable or crop productivity is at a low level. The maize yields in all four groups range between 0.65 t/ha and 2.6 t/ha (Q5-Q95) and are evenly distributed over the groups therefore similar yield changes will have a very different effect on local food security. This becomes evident when comparing yield changes with an indicator of food security like the number of people undernourished in a country (FAO, 2011b). Most parts of e.g. the Central African Republic are belonging to group B with only slight yield changes but 40 % of the population was undernourished in 2006-2008 making the country much more vulnerable to yield reductions compared to Uganda with most parts of the country indeed belonging to group C with higher yield decreases but less people undernourished today (22 %).

Uncertainty in GCM projections of precipitation

Although GCM projections agree on the level of median temperature increase, they project very different precipitation patterns in various regions of sub-Saharan Africa due to a large variety of model setting caused by the models' resolution and model physics, affecting e.g. the occurrence of convection or the vertical transport of moisture in the tropics (Lin, 2007). This influences the distribution of wet and dry days and the precipitation amount per wet day simulated in each GCM and in turn the severity of water stress in the growing season. There is some consistency between GCMs with respect to the projected increase of annual precipitation amount in East Africa and a drying in southern Africa. A consistent increase in the number of extremely wet seasons in West Africa and East Africa by 20 % and an increase of extremely dry seasons by 20 % in southern Africa combined with an increase in the rainfall intensity is also expected (Christensen *et al.*, 2007). Most of the GCMs project excessive precipitation over much of the tropics and, associated with that, insufficient precipitation over much of the Equatorial Pacific (Lin, 2007). This double-ITCZ (Inter-Tropical Convergence Zone) problem together with another common bias of GCMs, the too strong persistence of tropical precipitation (Lin *et al.*, 2006), might lead to poor representation of tropical precipitation patterns in some GCMs. An important element of tropical intra-seasonal variability and thus weather and climate forecasting between 15° N and 15° S, the Madden–Julian oscillation, is simulated nearly realistic from ECHAM5/MPI-OM and CNRM-CM3 (Lin *et al.*, 2006). These models were chosen for our study as well and provide the climate input data in 26% of all grid cells in the studied region.

Limitations of modeling stress on crop growth and development

The global dynamic vegetation model LPJmL considers the effects of water stress on crop growth and development and temperature effects on the photosynthesis rate and length of the growing period (as described in the section “Modelling the impact on agricultural vegetation”). Results from previous studies on heat stress effects on crop yields in sub-Saharan Africa indicate that the Sahel and southeastern Africa are most affected by heat stress (Teixeira *et al.*, in press) and that maize yields are negatively affected in areas with an annual mean temperature above 25 °C because daily temperatures commonly exceed 30 °C. A yield loss of 10 % per one °C of warming is possible in these regions (Lobell *et al.*, 2011). These results agree well with the large yield reductions of at least 33% in grid cells in the Sahel and parts of Southern Africa assigned to group A with an annual mean temperature above 28 °C and temperature increases of 2-3 °C in the 2060s. It is however not clear to what extent maize yield is reduced because of shortened development phases, leading to reduced light interception in an accelerated life cycle and because of a limited photosynthesis rate. This study does not consider several damaging effects of heat and water stress; on the other hand, the plants´ ability to develop heat and desiccation tolerance is also omitted. The study of Barnabas *et al.* (2008) gives an overview of these damaging effects which are also important for the growth and development of cereals but not considered in the model. Among the most important effects are oxidative damage, modifications in membrane functions, denaturation of existing proteins, reductions in pollen germination ability due to high temperatures (>30 °C) and the delay or even depression of flowering due to limited water supply. For maize, daily temperatures above 33.5 °C and 38 °C were shown to reduce the kernel growth rate and the pollen germination ability, respectively (Barnabas *et al.*, 2008).

The beneficial effect of elevated CO_2 concentrations on plant growth and above-ground biomass can be computed with LPJmL. This effect is not considered in the study, as its effectiveness is questionable for maize without large additional nitrogen inputs (Long *et al.*, 2006). The risk of crop damage due to increased temperature or water stress does not only depend on the magnitude of temperature and precipitation changes but also on the vulnerability of a region to these changes determined by current climatic conditions and farmer's management strategies for adaptation such as choosing an adapted sowing date or cropping system (Chapter 3). Selecting heat-resistant crop varieties is another adaptation option helping to reduce negative climate change impacts considerably e.g. in Mali, Butt *et al.* (2005) showed that heat-resistant maize varieties simulated with EPIC are less affected from climate change i.e. yields are reduced by 8.6 % compared to a reduction of 11.2 % without adaptation for HadCM3. Also applying water-harvesting techniques (Rost *et al.*, 2009) and increasing rainwater productivity through conservation farming strategies (Rockström *et al.*, 2009) might lower the damage on crop yield considerably and are sometimes very cost-effective at the same time (Ebi *et al.*, 2011).

4.5. SUMMARY AND CONCLUSIONS

We show that the importance of the agro-climatic variables temperature, wet season precipitation and wet season length for maize growth, varies in space depending on the initial climate conditions and the magnitude of climate change. Crop yields change considerably in regions with unsuitable or extreme growing conditions which are very susceptible to even slight climate change and in regions which are exposed to strong temperature and precipitation changes. The regions most vulnerable to temperature increases are southern Africa and parts of East and West Africa with annual mean temperatures of 18-24 °C which are exposed to annual temperature increases of 2-3 K leading to maize yield decreases of more than 20 %. Parts of South Africa, Zimbabwe, Mozambique and the Sahel with higher annual mean temperatures above 28 °C are exposed to extreme daily temperatures but the temperature effect in the model is similar to the effect in regions with cooler temperature. This indicates that in the model increasing temperatures only affect the crop by shortening the growing season and limiting photosynthesis but that damage from extreme daily temperatures above 30 °C is largely underestimated in the model. The same regions are even more susceptible to precipitation changes as they have short (< 120 days) and dry (< 500 mm) growing seasons and reduced wet season precipitation leads to maize yield reductions of 30 % and more. In the mountainous regions of South Africa and East Africa temperature increases are beneficial for maize growth and lead to increasing crop yields of up to 20-30 %. These findings should be considered in drought and heat stress breeding programmes and in studies on adaptation to climate change impacts. With climate change both, temperature and precipitation will change but determining the limiting effect helps to prioritize future research needs and to identify adequate crop varieties and adaptation options in different environments.

The model is sensitive to all three agro-climatic variables wet season length, wet season precipitation and temperature but reductions of crop yields mostly arise from changes in temperature and wet season precipitation. A shortened wet season does not affect maize growth in most parts of sub-Saharan Africa as maize is simulated to grow at the beginning of the wet season and mostly reaches maturity before the end of the wet season. Only in small parts of southern Africa and the Sahel with a wet season length not exceeding 100 days, maize yields are reduced because of a shortened wet season. The effect of a reduced wet season length would be much stronger in multiple cropping regions where the second crop is at higher risk to be influenced negatively from a shorter wet season. However, African farmers which tend to be risk-averse will rather avoid a second cropping cycle that coincides with the end of the wet season.

4.6. ACKNOWLEDGEMENTS

We acknowledge the modeling groups, the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP's Working Group on Coupled Modelling (WGCM) for their roles in making available the WCRP CMIP3 multi-model dataset. Support of this dataset is provided by the Office of Science, U.S. Department of Energy. We thank Sebastian Ostberg and Jens Heinke for preparing the LPJmL input data on temperature and cloudiness and Jens Heinke for providing the WATCH forcing data. We are also grateful to Jan Philipp Dietrich for his comments on the scenario setting and the discussion of the results.

4.7. AUTHORS´ CONTRIBUTION

The contribution of the different authors was as follows: K.W. and C.M. conceived the original idea of studying the effects of changing precipitation variability on crops. K.W. expanded this into a study on separating the effects of temperature and precipitation on crops. C.M. prepared the daily precipitation files from 18 GCMs, which was the basis for analysing changes in the wet season length and precipitation. All authors were involved in developing and discussing the methodology. K.W. prepared the precipitation input files, did the model runs, prepared the figures, did literature research and wrote the manuscript. All authors were involved in discussing the results and reviewing the manuscript several times.

5. General Conclusions

In this chapter I first briefly summarize the key results and conclusions related to the objectives of this thesis presented in the introduction. In addition, I recommend future research needs which arise from the findings presented in the main chapters and from my experience of modeling climate change impacts.

5.1. KEY RESULTS AND CONCLUSIONS

Agricultural crops are projected to be severely impacted by climate change in many parts of sub-Saharan Africa, depending on the (i) magnitude of climate change and (ii) depending on the crop, the cropping system and the adaptive capacity of farmers in a region. The most important results from chapter 3 and 4 on the impacts of climate change on agricultural crops and their determining factors are:

1. The aggregated crop yields in sub-Saharan Africa are projected to decline by 6-24 % in the 2085s depending on the climate scenario, cropping system and adaptation options.

2. Analysing the effects of changes in individual agroclimatic variables separately makes it possible to understand their regional importance for overall crop yield changes and to identify the limiting effect for food production in each region

3. Southern Africa is clearly the region most susceptible to climate change, especially to precipitation changes, but also the region with the largest variability in crop yield changes.

4. The Sahel north of 13° N and parts of Eastern Africa with short growing seasons below 120 days and limited wet season precipitation of less than 500 mm are also vulnerable to precipitation changes.

5. In most parts of Central and East Africa with longer growing seasons, in contrast, the effect of temperature increase on crops overbalances the precipitation effect and is most pronounced in a band stretching from Angola to Ethiopia in the 2060s. With even stronger temperature increases until the 2085s parts of Western Africa south of 13° N are also impacted stronger.

By applying certain management strategies for adaptation, farmers are potentially able to reduce the negative effects of climate change on crops and minimize the risk of crop failure by applying low-tech adaptation strategies. The most important results from chapter 2 and 3 show the potential of management strategies for adaptation the farmers might benefit from.

1. Crop yields are simulated to be higher and therefore food production in sub-Saharan Africa would be less susceptible to climate change if the crop's sowing date is adapted to shifts of the rainy season. This is already an effective adaptation option to current climate variability (+°6-8 %), but it becomes even more important under climate change (+ 11-17 %). Sowing dates for global crop models can be satisfactorily estimated from climate conditions with only one month deviation to observed sowing dates in most of the locations but with some uncertainty for tropical systems with high cropping intensities. The proposed method therefore is suitable for global crop models and for climate change assessment studies which should consider this management option.

2. Crop yields are simulated to be higher also if a second crop cultivar in a sequential cropping system can be cultivated (+ 67-77 %) in regions with a long growing season and if farmers have sufficient input and labour available for a second cropping cycle. As a precondition for achieving this result I show the distribution of the most important multiple cropping systems in ten African countries and give evidence that farmers prefer to grow short-growing crop cultivars in these systems in order to reduce the risk of crop failure.

3. Choosing the highest-yielding cropping system might lower negative climate change impacts as well (+ 24-29 %). As this beneficial system might be an uncommon or even unknown cropping system in a region and not necessarily the traditional cropping system, its application might be limited. Also farmer decide on the crops and cropping systems according to local biophysical or socio-economic conditions which are not considered here.

Not only in sub-Saharan Africa but also on a global scale these management strategies have the potential to increase the crop production in the same range as water management strategies. Rost *et al.* (2009) showed the global potential of two water management strategies like collecting rainwater in cisterns, ponds or small dams (“rainwater harvesting”) or soil and water conservation methods which increase the water availability for plants (“vapour shift”). Applying these management strategies globally would increase crop production by more than 50 % under the present climate (Rost *et al.*, 2009), and by more than 30 % under changing climate in the most optimistic scenario (Figure 5-1). This is a theoretical potential of soil and water conservation methods increasing the transpiration-to-evaporation ratio to 85 %. In a moderate scenario, water management strategies increase crop production by 4-13 % which is comparable to 6-12 % increases for sowing date and cropping system adaptation and both are close to the achievable production increase from irrigation (Figure 5-1). Assuming that in sub-Saharan Africa and other developing regions the water management strategies are least efficient, crop production would still increase by 1.5-4.6 % (Figure 5-1).

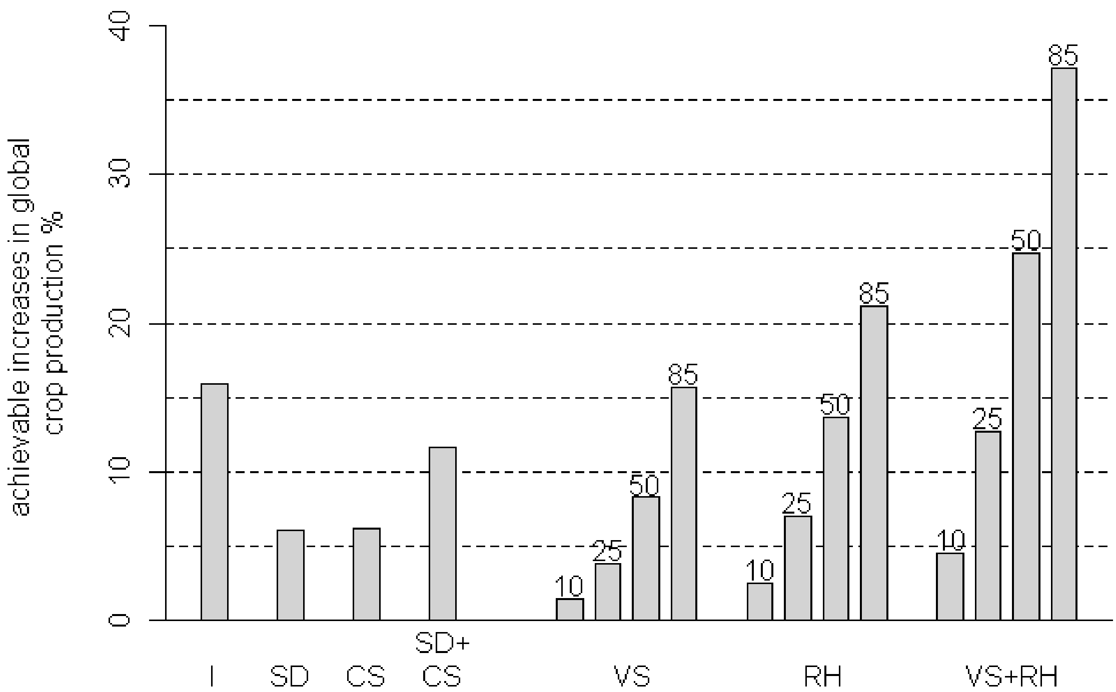

Figure 5-1 Achievable increases in global crop production (%) through different water management and cropping system management strategies under climate change in the 2055s as compared to the current state: I Irrigation, SD adapted sowing dates, CS adapted cropping system, SD+CD sowing dates and cropping system adaptation, VS Vapor shift with different efficiency levels (10-85 % increase in plant transpiration), RH rainwater harvesting with different efficiency levels (10-85 % rainwater stored), VS+RH Vapor shift and rainwater harvesting with different efficiency levels (Rost *et al.*, 2009; Waha *et al.*, 2011).

5.2. FUTURE RESEARCH PRIORITIES

From the results and conclusions of this thesis it is possible to continue with several next steps and I consider three topics to be the most important future research needs.

Up-scaling multiple cropping data to global scale

As I showed in chapter 3, multiple cropping is a common and widespread management strategy to increase crop production, to lower the risk of total crop failure and to minimize the negative effects of climate change in some regions. Considering multiple cropping also in global studies about climate change impacts on agriculture would enhance the reliability of these results considerably as adapting the cropping system might be a suitable adaptation option in other world regions as well. The first step would be to prepare a global land use dataset including multiple cropping systems and fallow land, which is not available yet. Global land use data sets (e.g. Portmann *et al.*, 2010) can be combined with available regional datasets on multiple cropping zones in India (Frolking *et al.*, 2006), China (Frolking *et al.*, 2002) or Africa (chapter 3) and related data on e.g. farming and livelihood systems in Africa (Thornton *et al.*, 2006) or cropping calendars in Africa (FAO, 2010), which are based on satellite data or agricultural surveys. This is a demanding task already, as the different datasets will probably disagree in some regions. If information on existing multiple cropping systems is still missing, the farmers choice of crops and cropping systems can also be modeled as a function of climate conditions, soil properties, expected profit and household characteristics (Kurukulasuriya & Mendelsohn, 2006; Seo & Mendelsohn, 2008), considering that in developing countries farmers might give a higher priority to stable food supply than to high profit. Secondly, model parameters for a global application need adjustment as shown in chapter 3.2 for Africa in order to represent shorter cropping cycles in a multiple cropping system. Farmers clearly prefer long-growing crop cultivars in single cropping systems and short-growing crop cultivars in sequential cropping systems.

Analyse the effect of abiotic stress factors on crops

Large-scale crop models simulate the effect of a few abiotic stress factors like extreme high or low temperatures, low water availability, nitrogen and phosphorus deficiency and oxygen deficiency in the soil on crop growth and development (

Table 5-1). However, most of them consider only some of these stress factors, only partly simulate their effect on crop growth, are only validated for a limited number of sites or with little data, while other abiotic stress factors like salt stress, heavy metal pollution of soils and water, aluminum toxicity or ozone damage (Larcher, 1995) are not considered at all.

Table 5-1 Abiotic stress factors considered in large-scale models simulating agricultural vegetation.

Model	**Stress factor**
DSSAT	high and low temperatures (no frost damage), low water availability, nitrogen deficiency (Jones *et al.*, 2003)
DayCent	high and low temperatures (no frost damage), low water availability, nitrogen deficiency (Stehfest *et al.*, 2007)
LPJmL	high and low temperatures (no frost damage), low water availability (Bondeau *et al.*, 2007)
GEPIC	high and low temperatures, low water availability, nitrogen and phosphorus deficiency and oxygen deficiency in the soil (Kiniry *et al.*, 1995; Liu *et al.*, 2007)
ORCH-mil/ORCHIDEE-STICS	high and low temperatures (no frost damage), low water availability, (Berg *et al.*, 2010), nitrogen deficiency (only ORCHIDEE-STICS, Gervois *et al.*, 2004)
Pegasus	high and low temperatures (no frost damage), low water availability, nitrogen deficiency (Deryng *et al.*, 2011)

For this reason, crops are very robust against abiotic stress factors in the models and further development and validation of stress effects on crops will improve the reliability of model results. With climate change and higher risk of extreme events occurring in many regions, heat and water stress effects especially will become more important in climate change impact studies. It is expected that under enhanced atmospheric greenhouse gas concentrations, return periods of extreme precipitation events will become shorter while precipitation intensity and the number of wet spells as well as the frequency of high temperatures will increase in most areas (McGuffie *et al.*, 1999). I already showed the effect of high temperatures and low wet season precipitation and their regional importance in chapter 4. These results should also be discussed in the light of additional stress factors and the potentially beneficial CO_2 fertilization effect, preferably for different crops, crop varieties and management treatments. Field trial data from the CGIAR centers on agricultural research are most suitable for this purpose, e.g. for tropical maize from 123 African research stations, four crop varieties and five management regimes managed from the International Maize and Wheat Improvement Center (CIMMYT) and others, which is available for the period 1999 to 2007 (Bänziger *et al.*, 2006; Lobell *et al.*, 2011). Another source of crop yield data under different management is the household survey used in chapter 3 containing more than 8600 households in ten African countries (Dinar *et al.*, 2008) and agricultural census data for individual countries, e.g. for Uganda (Fermont & Benson, 2011). Building a database combining these data will be a first important step.

Bridging the gap between model scales

Farmers decide on the best management strategy depending on local environmental and economic conditions and accordingly act on a local scale, while large-scale crop models like LPJmL focus on global or regional dynamics. In a decision making process on how to develop the agricultural sector also under climate change a study at a large scale can only be a first step for understanding the long-term and large-scale limitations for agriculture in a region. To serve as a decision support tool on a local scale a crop model needs to be adjusted to local soil and climate conditions and validated using local agricultural data. Combining regional and global crop models might be an option for bridging a gap between the two scales. Field or point models suitable for simulating crop growth at a local scale often include a wide range of management options and crop cultivars but require a lot of local knowledge and parameters which are mostly not available on the global scale. Crop models on a local scale can however provide knowledge about the most important drivers of crop response to changing climate and improve model parameters considerably. These findings then need to be assigned to a larger scale by e.g. assuming similar limitations and processes in locations with similar growing conditions. This will be the most challenging part but a hierarchical cluster analysis to group individual points to regions with similar crop response to climate seems to be a promising approach for this. Several crop models were already applied in simulation studies in the tropics on a local scale like e.g. APSIM (Keating *et al.*, 2003), CropSyst (Stöckle *et al.*, 1994), GLAM (Challinor *et al.*, 2005), RIDEV (Dingkuhn *et al.*, 1995), SARRA-H (Dingkuhn *et al.*, 2003), STICS (Brisson *et al.*, 2003).

From the results of my thesis I also conclude, that the following needs to be considered in climate change impact studies by all means:

The context of food (in)security: In order to report on the progress made towards achieving the World Development Goal of reducing the number of undernourished people by half by the year 2015, the FAO started to publish the series “The state of food insecurity in the world” in 1999. Countless governmental and non-governmental organizations are engaged in monitoring and analysing the situation of countries and people facing a high risk of undernourishment and hunger, which is largely a political and economical problem. In addition to the main drivers of food insecurity, weak governments, insufficient investment in agricultural technology, economic crises, missing safety nets and social programmes and violent conflicts, to name but a few, climate change poses a risk to vulnerable societies and the agricultural sector. It therefore becomes part of the complex problem to achieve food security and develop the agricultural sector making it a highly relevant topic connected to political and economical topics. This requires good communication of the key results, limitations and conclusions of a climate change impact study on agriculture to stakeholders.

Data quality and availability: The most important input data for a global model simulating agricultural crops are climate data, soil data and data on land use und management intensity. Comparing the amount of land already cultivated to the amount of land assessed as potentially cultivable land in sub-Saharan Africa indicates that there is huge potential for cropland expansion into areas currently not used (Fischer *et al.*, 2011). However, the amount of cultivated land might be underestimated and the land with potential for cultivation might be overestimated considerably. The estimates of total cropland in sub-Saharan Africa in 1988/90 published in the FAO study “World agriculture towards 2010” needed adjustments of 51 % and estimates on the proportion of land cultivated in Africa still differ between different sources from 18% to 26% (Young, 1999). Reasons for this uncertainty in cropland estimates are oversimplifications in global soil maps, the questionable nature of land use statistics especially in developing countries and neglecting the demand for land for non-agricultural purposes. Young (1999) therefore suggests that "estimates of the total spare land in the developing world, and those for individual countries, should be reduced to half or less the values given" (p.17). In order to enhance the representation of agricultural area in global land use data sets, MIRCA2000 (Portmann *et al.*, 2010; Portmann *et al.*, 2008) and SPAM2000 (You *et al.*, 2009) were developed recently. These two datasets are currently the most comprehensive global datasets combining existing data with national and sub-national agricultural statistics and surveys and both are accessible via their project web pages. SPAM2000 reports crop area and production on a sub-national level and also distinguishes between three levels of input systems: irrigated, rainfed high-input/commercial, and rainfed low-input/subsistence. MIRCA2000 also distinguishes between rainfed and irrigated crop area and additional reports crop calendars for 26 crops. Both datasets are the most comprehensive global datasets on cropland distribution at the moment.

Presentation and aggregation of model results: The magnitude of crop yield changes reported in climate change impact studies depends on the aggregation level, as negative climate change effects might be counterbalanced by positive effects if the aggregation units are too heterogeneous and extremes are not visible anymore. On the other hand it is important to aggregate results for comparisons between countries, world regions and time periods. Cluster analyses might be an appropriate tool for finding homogenous units as proposed for regional climate change results (Mahlstein & Knutti, 2010), global-land use patterns (Dietrich, 2011) and crop yield changes due to climate change in this thesis (chapter 4).

Summary

Agriculture is one of the most important human activities providing food and more agricultural goods for seven billion people around the world and is of special importance in sub-Saharan Africa. The majority of people depends on the agricultural sector for their livelihoods and will suffer from negative climate change impacts on agriculture until the middle and end of the 21st century, even more if weak governments, economic crises or violent conflicts endanger the countries' food security. The impact of temperature increases and changing precipitation patterns on agricultural vegetation motivated this thesis in the first place. Analysing the potentials of reducing negative climate change impacts by adapting crop management to changing climate is a second objective of the thesis.

As a precondition for simulating climate change impacts on agricultural crops with a global crop model first the timing of sowing in the tropics was improved and validated as this is an important factor determining the length and timing of the crops´ development phases, the occurrence of water stress and final crop yield. Crop yields are projected to decline in most regions which is evident from the results of this thesis, but the uncertainties that exist in climate projections and in the efficiency of adaptation options because of political, economical or institutional obstacles have to be considered. The effect of temperature increases and changing precipitation patterns on crop yields can be analyzed separately and varies in space across the continent. Southern Africa is clearly the region most susceptible to climate change, especially to precipitation changes. The Sahel north of 13° N and parts of Eastern Africa with short growing seasons below 120 days and limited wet season precipitation of less than 500 mm are also vulnerable to precipitation changes while in most other part of East and Central Africa, in contrast, the effect of temperature increase on crops overbalances the precipitation effect and is most pronounced in a band stretching from Angola to Ethiopia in the 2060s.

The results of this thesis confirm the findings from previous studies on the magnitude of climate change impact on crops in sub-Saharan Africa but beyond that helps to understand the drivers of these changes and the potential of certain management strategies for adaptation in more detail. Crop yield changes depend on the initial growing conditions, on the magnitude of climate change, and on the crop, cropping system and adaptive capacity of African farmers which is only now evident from this comprehensive study for sub-Saharan Africa. Furthermore this study improves the representation of tropical cropping systems in a global crop model and considers the major food crops cultivated in sub-Saharan Africa and climate change impacts throughout the continent.

Appendices

A ANALYSIS OF SOWING DATE PATTERNS OF ELEVEN CROPS

For each crop three maps show the a) difference between simulated sowing dates and observed sowing dates, b) simulated sowing date, c) observed sowing dates according to MIRCA 2000 (Portmann *et al.*, 2008). White colours indicate crop area smaller than 0.001 % of grid cell area. Sowing dates in regions without seasonality are not shown.

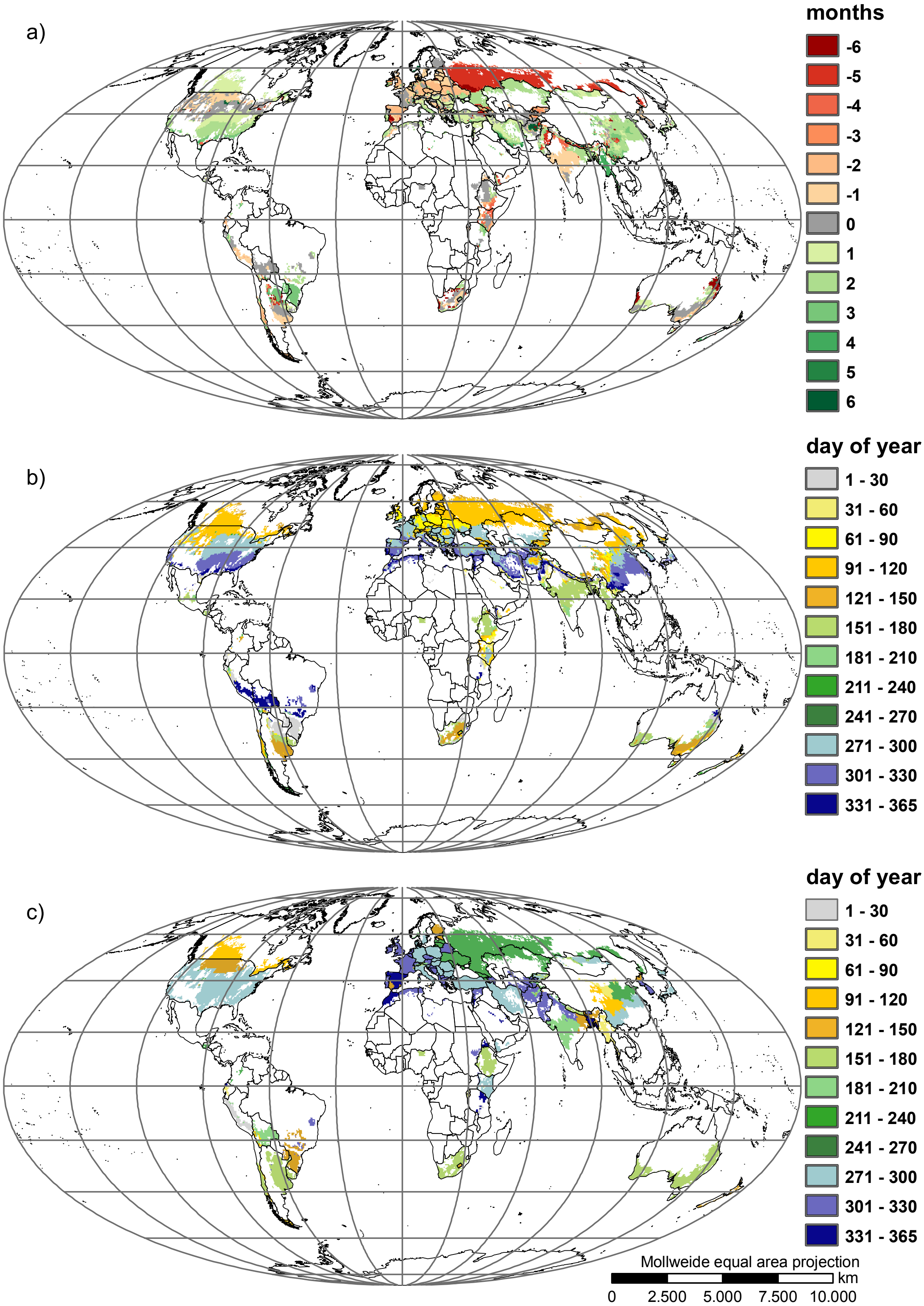

Figure A-1 Analysis of sowing date patterns of wheat.

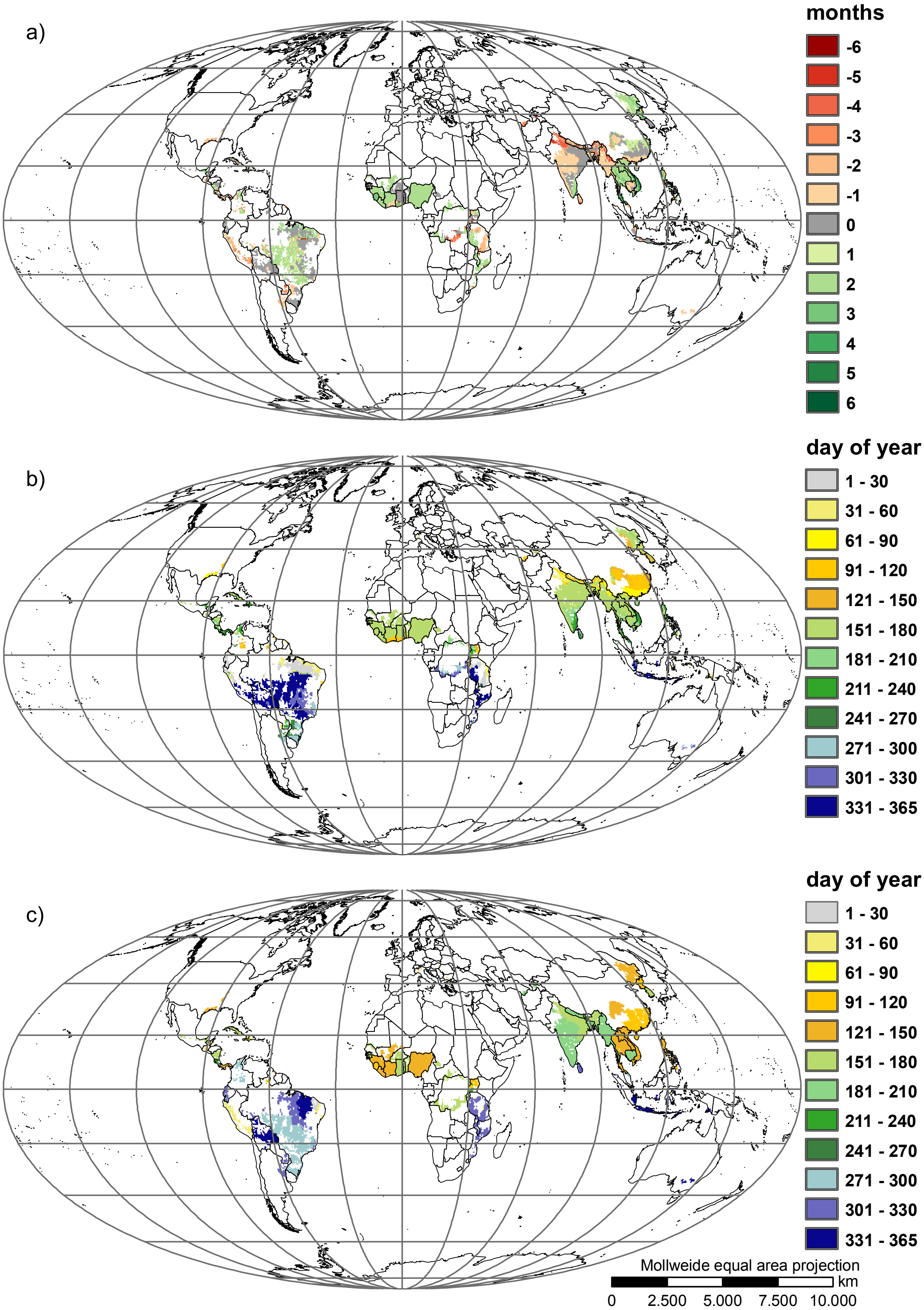

Figure A-2 Analysis of sowing date patterns of rice.

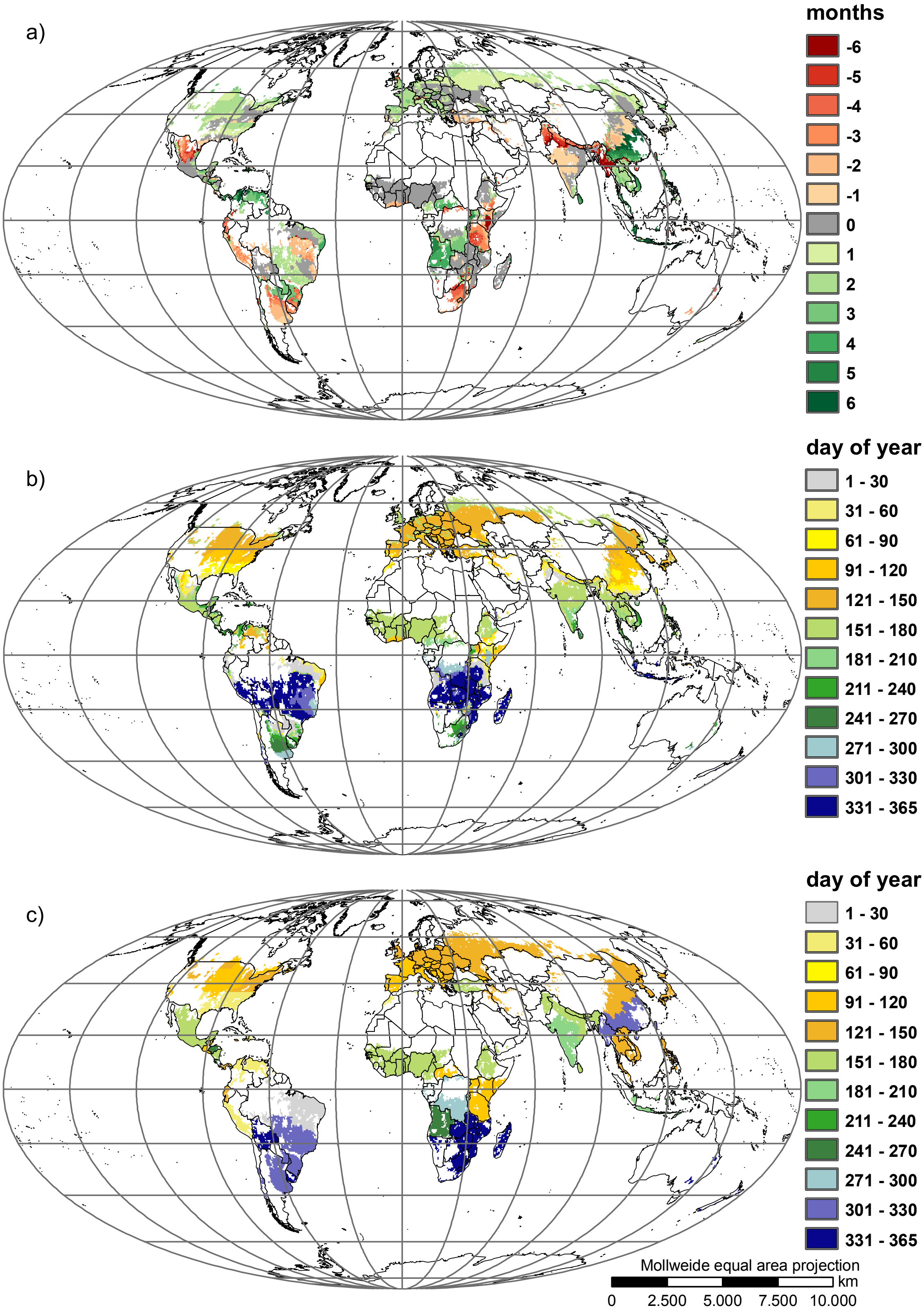

Figure A-3 Analysis of sowing date patterns of maize.

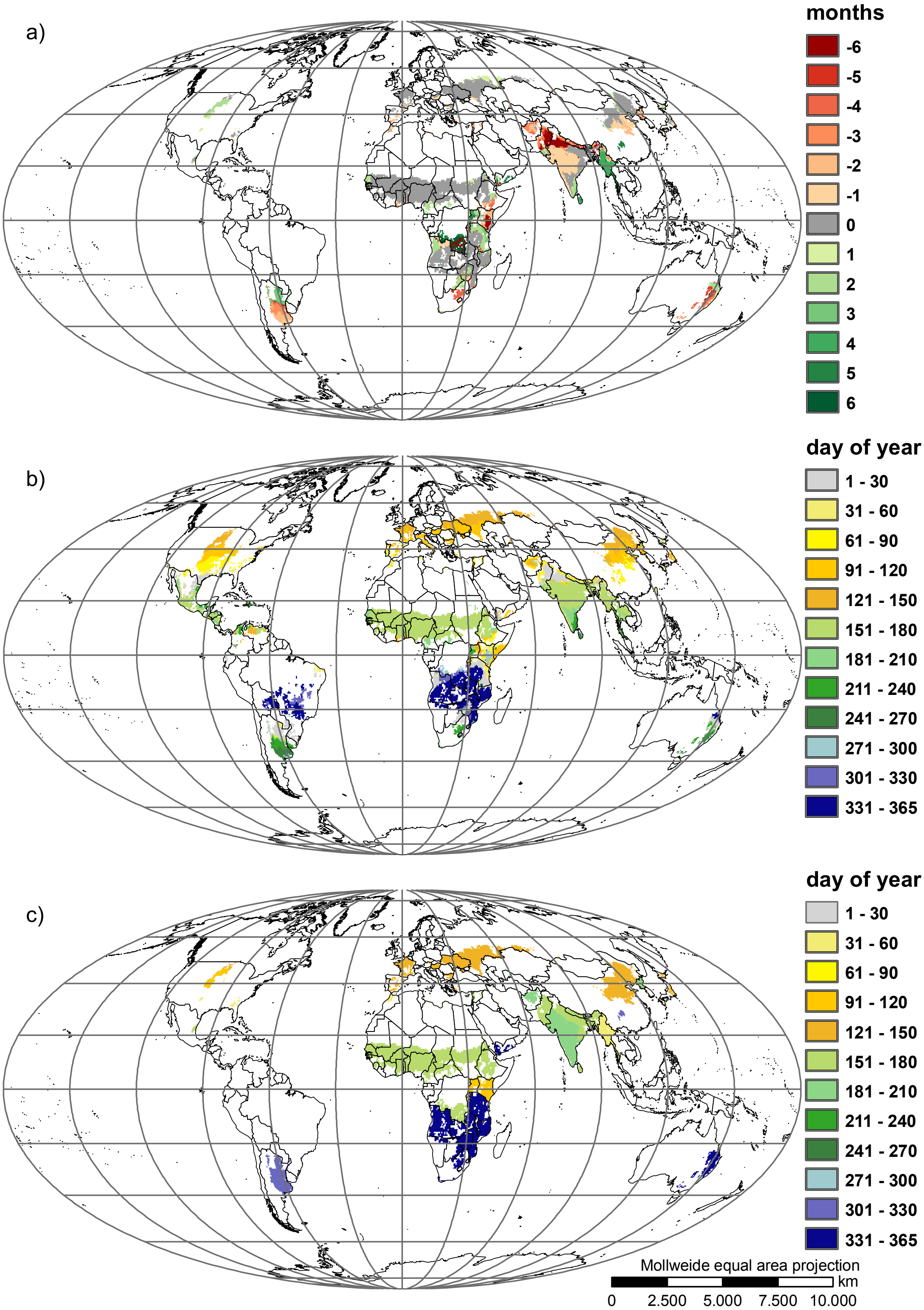

Figure A-4 Analysis of sowing date patterns of millet.

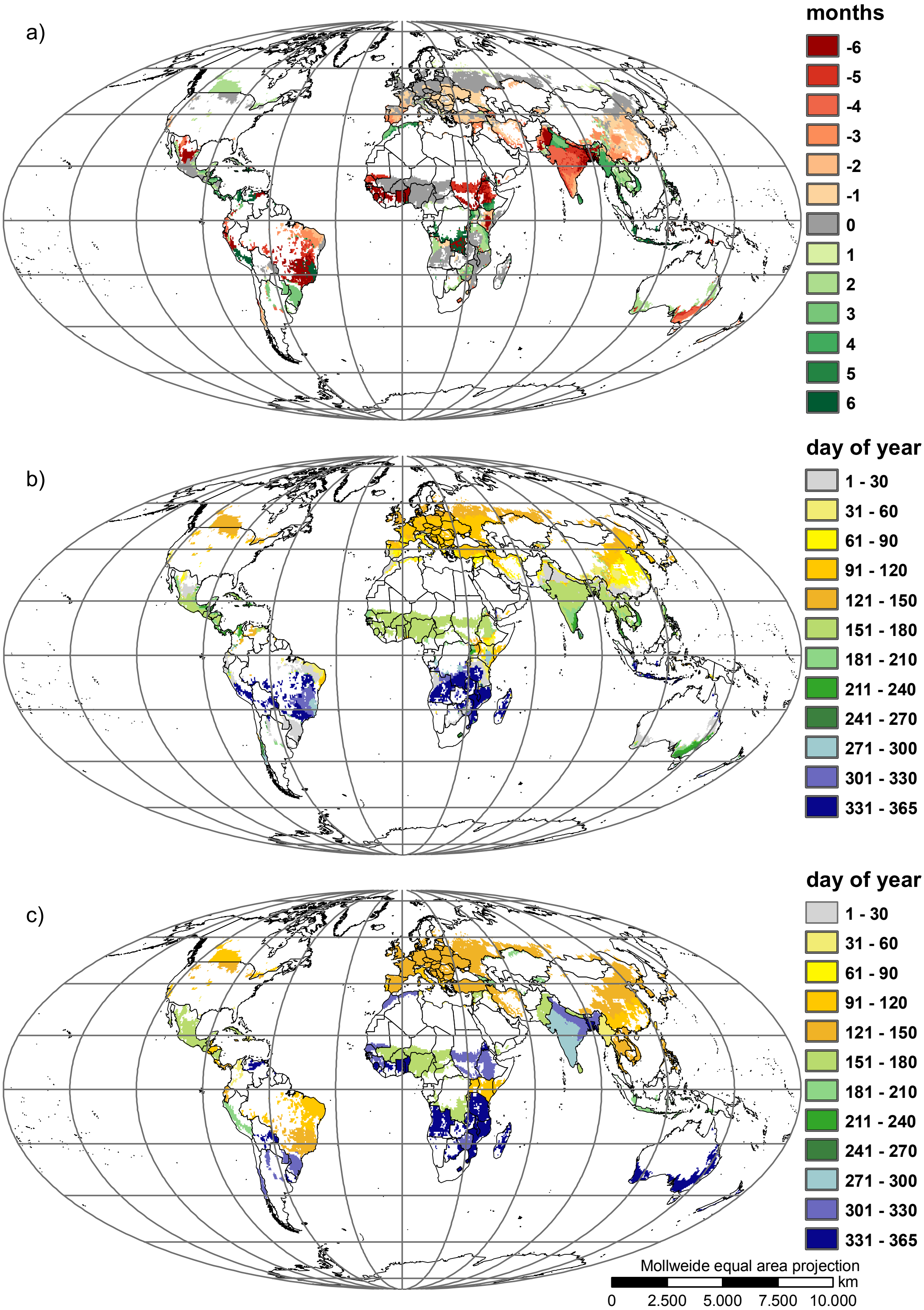

Figure A-5 Analysis of sowing date patterns of pulses.

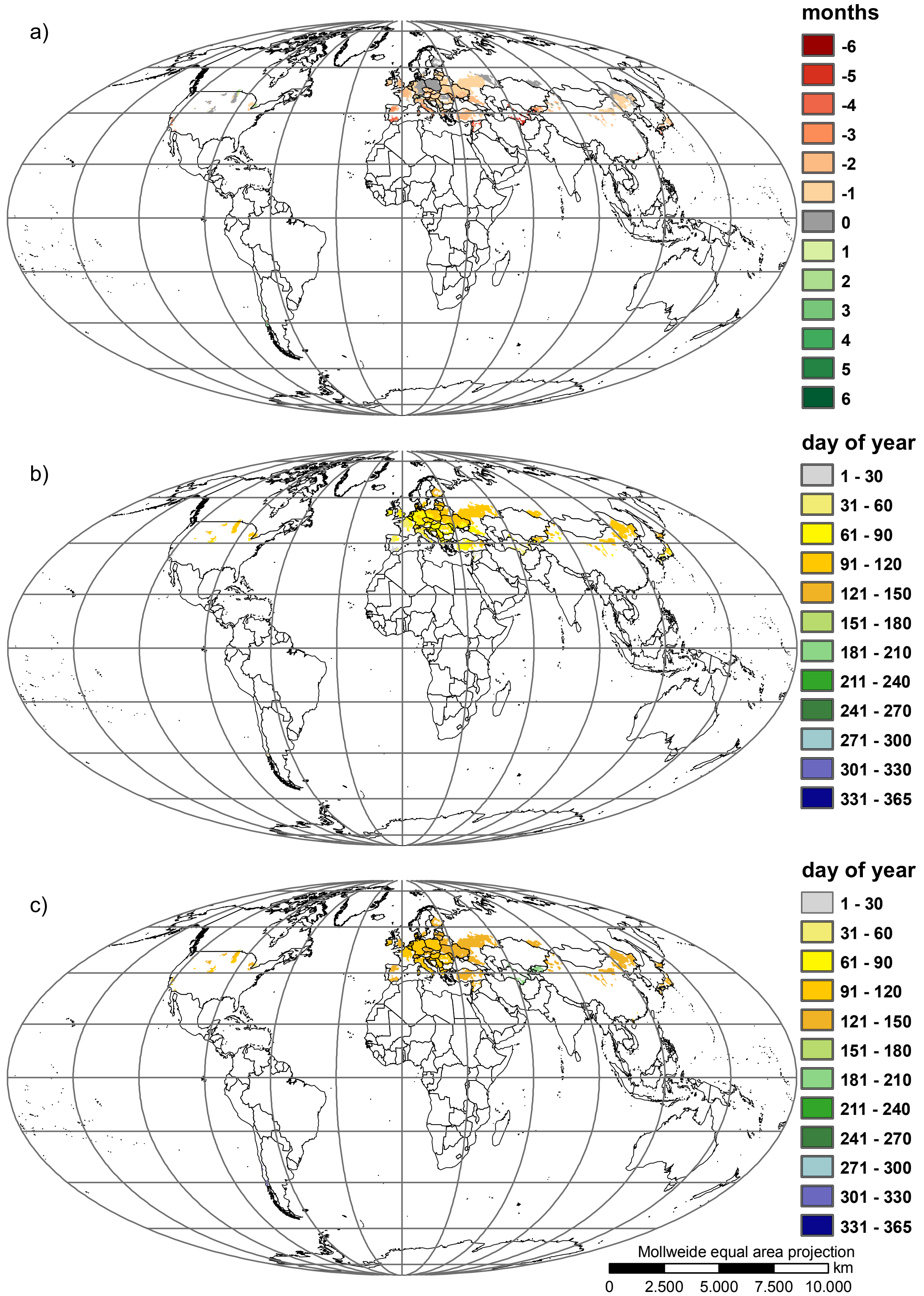

Figure A-6 Analysis of sowing date patterns of sugar beet.

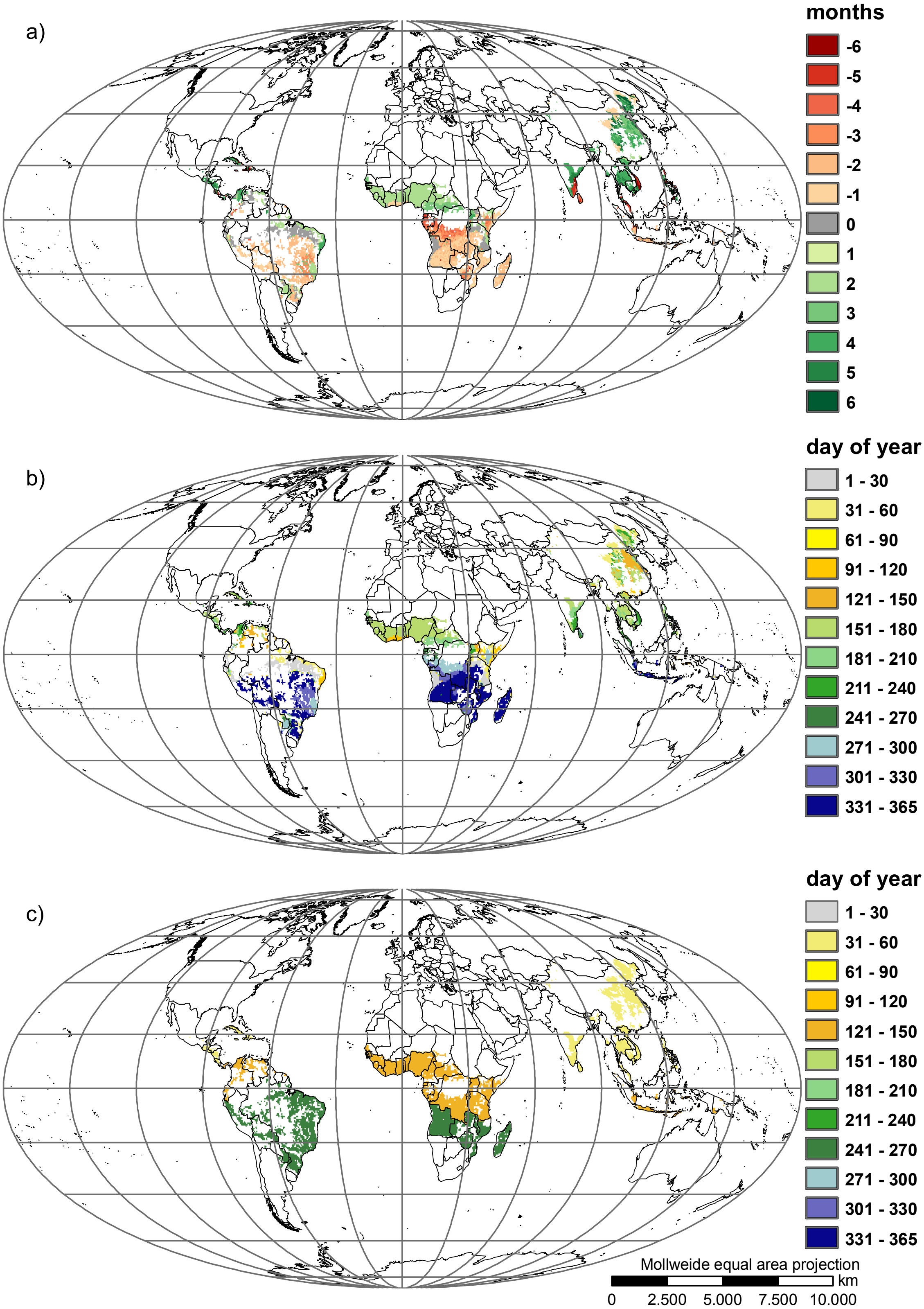

Figure A-7 Analysis of sowing date patterns of cassava.

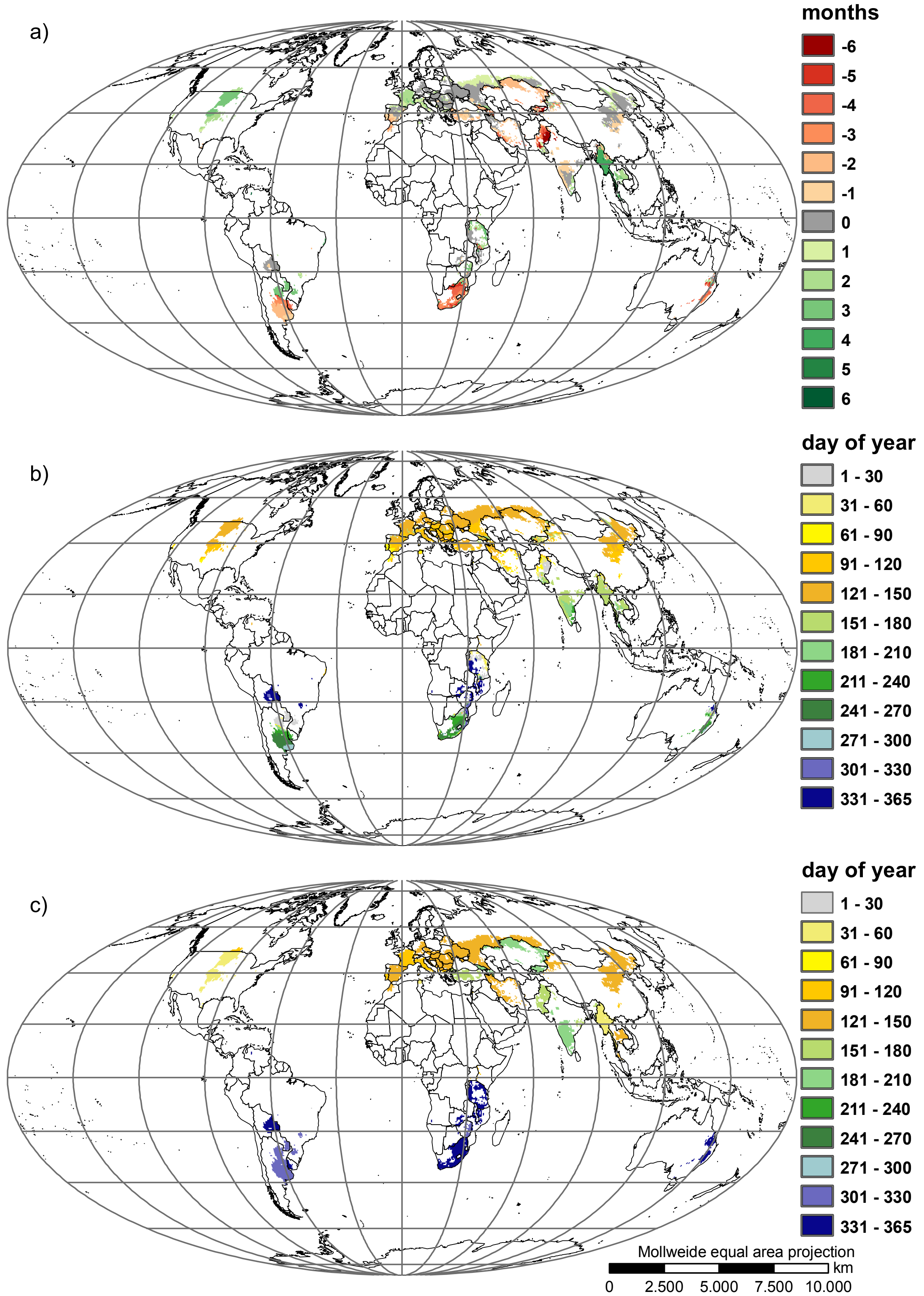

Figure A-8 Analysis of sowing date patterns of sunflower.

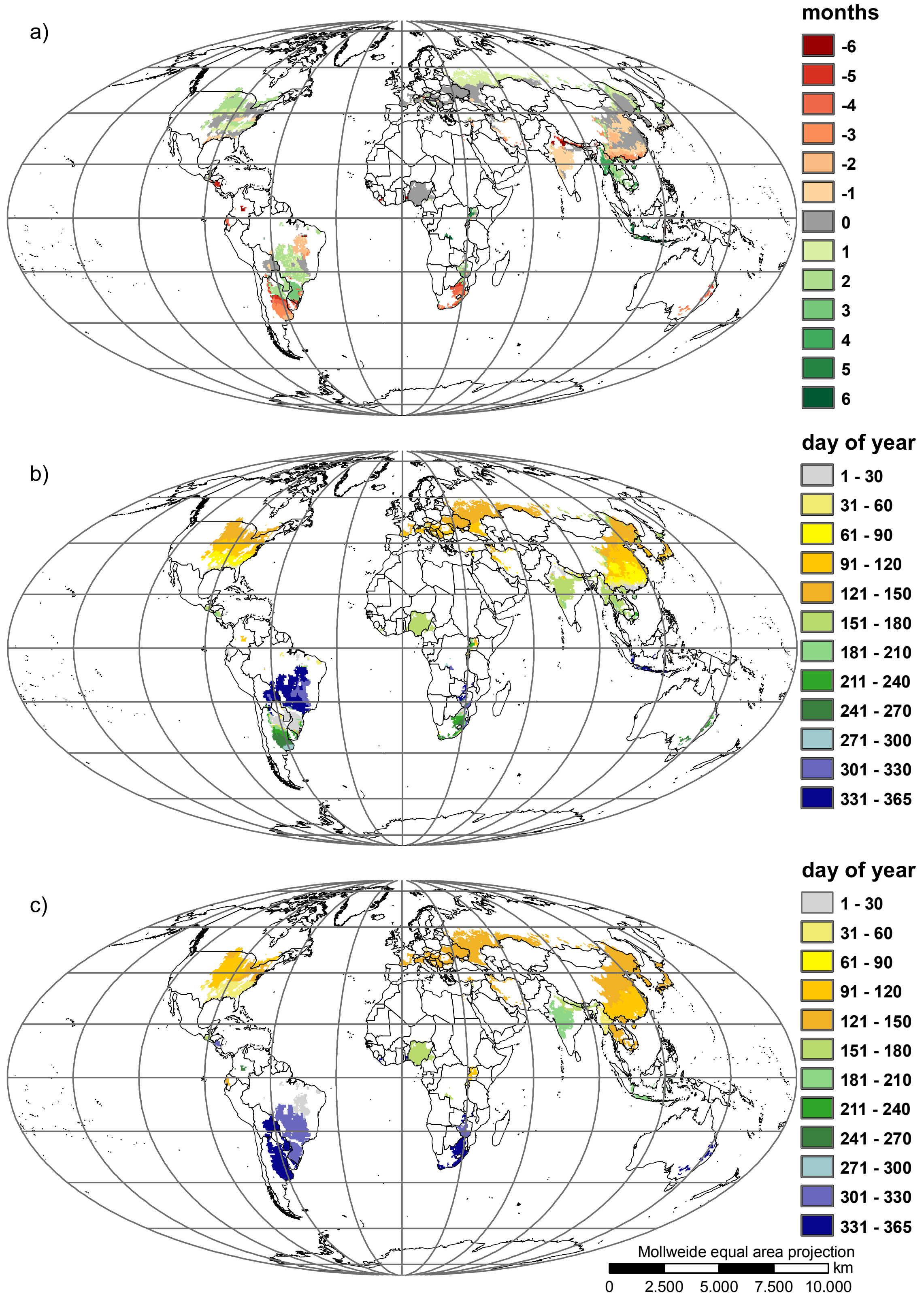

Figure A-9 Analysis of sowing date patterns of soybean.

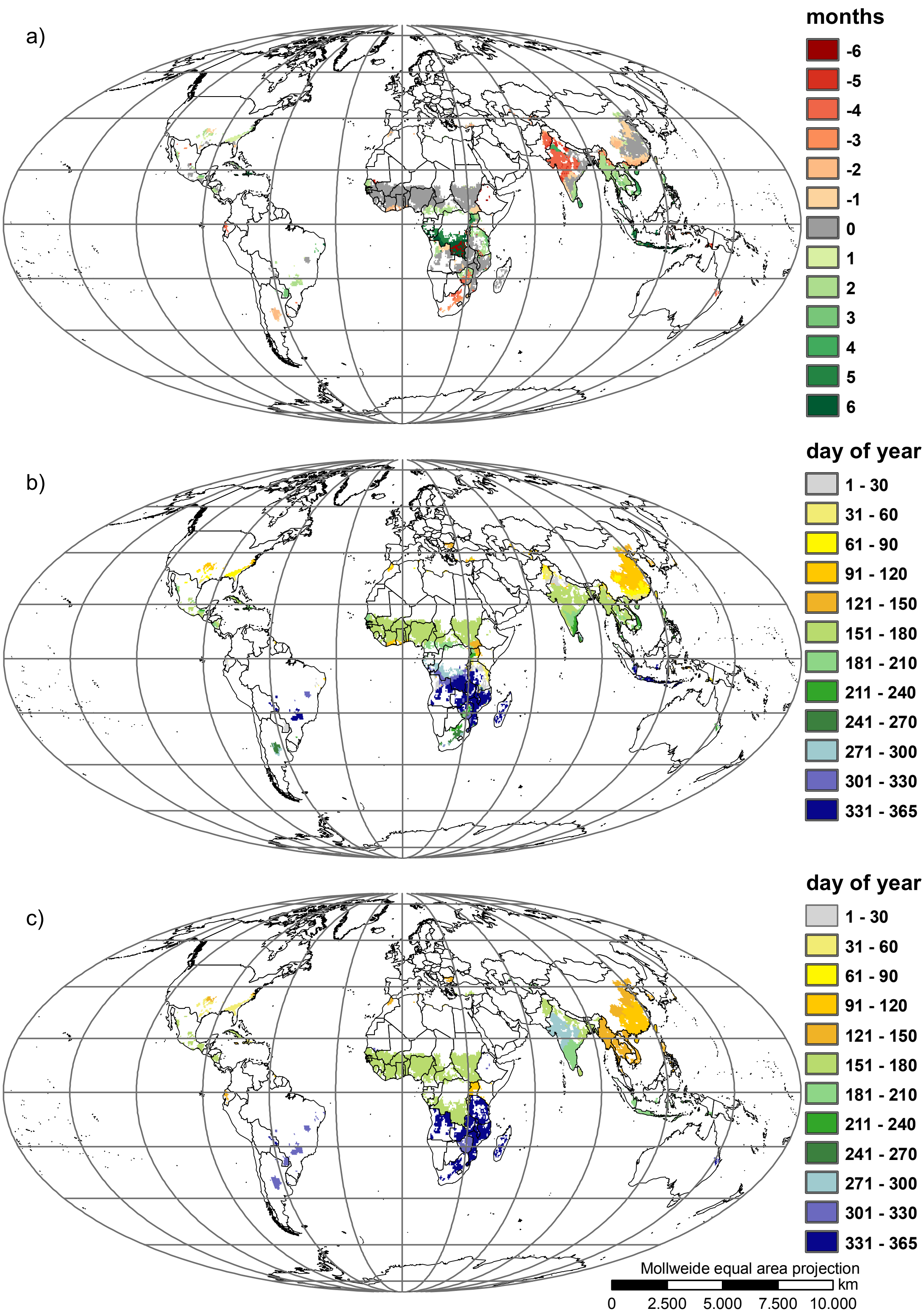

Figure A-10 Analysis of sowing date patterns of groundnut.

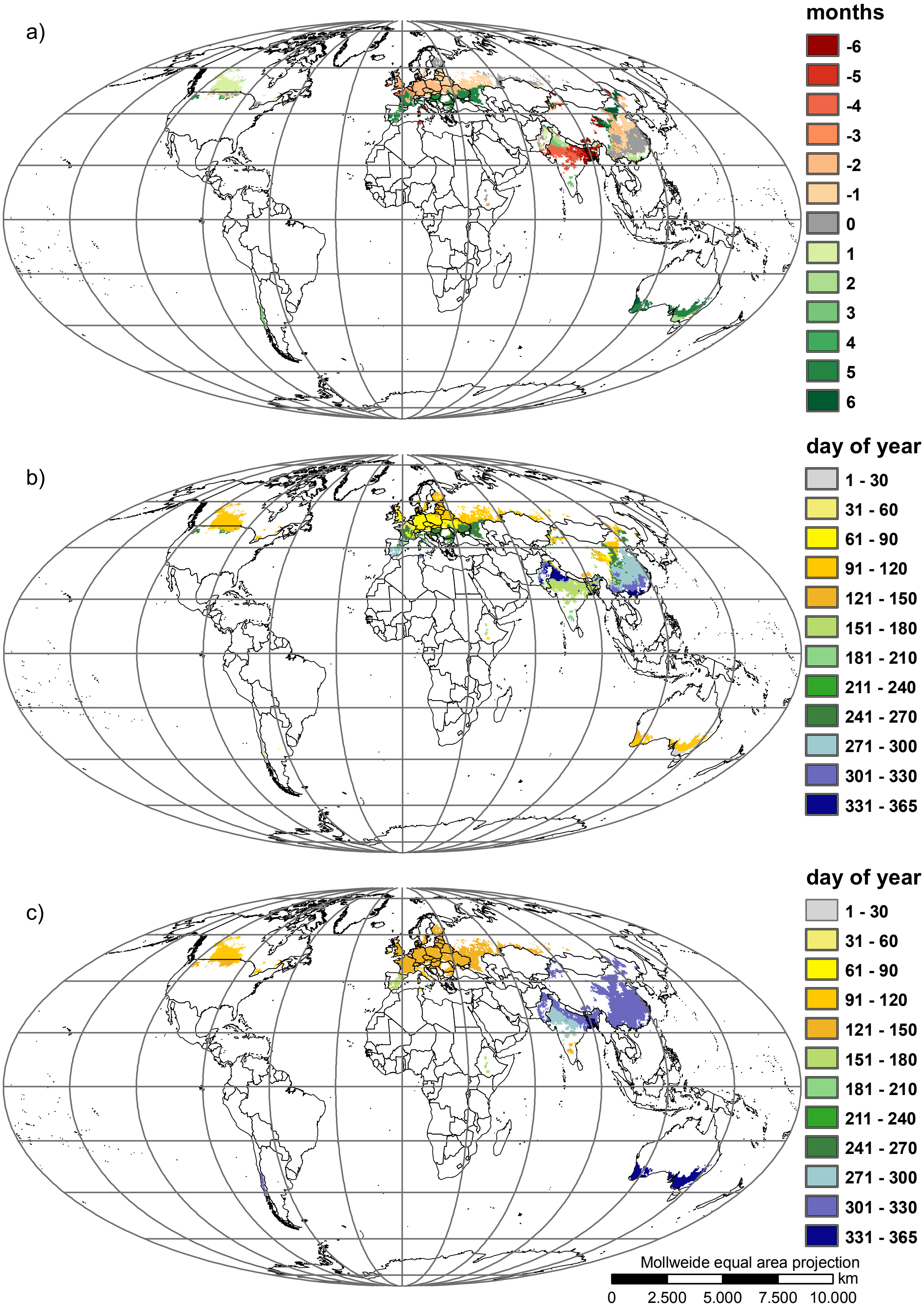

Figure A-11 Analysis of sowing date patterns of rapeseed.

B SENSITIVITY ANALYSIS OF CROP YIELD ON SOWING DATE

Methodology

A possible application of sowing dates simulated with the presented methodology is to provide global crop growth models under future conditions with suitable cropping windows. We tested the sensitivity of the LPJmL dynamic global vegetation and crop model for different sowing dates on simulated crop yields for five locations with different seasonality types, using maize as an example crop.

In LPJmL, crop growth is simulated using a combination of processes (photosynthesis, respiration, evapotranspiration, and leaf area development) on a daily basis (for more details, see (Bondeau *et al.*, 2007). LPJmL does not consider the effects of extreme temperatures on crop growth and development, e.g. frost damage. Phenological development of maize is simulated by accumulating temperature above the maize-specific base temperature (8°C) until maturity is reached, taking into account the effect of photoperiod, as applied in the AFRCWHEAT2 model (Ewert *et al.*, 1996), until anthesis. It was assumed for the five locations that farmers grow cultivars which are adapted to their environment. Required temperature sums till maturity per location-specific cultivar were calculated based on observed sowing and harvest dates, monthly temperature data from the year 1998, and photoperiods. Equal sensitivity to photoperiod between the cultivars was assumed (the optimum photoperiod was assumed to be 12.5h and the base photoperiod 24h). Yield was simulated for each location for a range of sowing dates (52, starting at the first of January, with steps of 7 days) for rainfed conditions, using the monthly climate data of the year 1998, and assuming that farmers grow the same cultivar throughout the whole year. The crop was allowed to grow for a period of maximum 250 days.

Results and Discussion

In Figure B-1, we display simulated maize yields per sowing date for the five locations, compared to the maximum simulated maize yield per location.

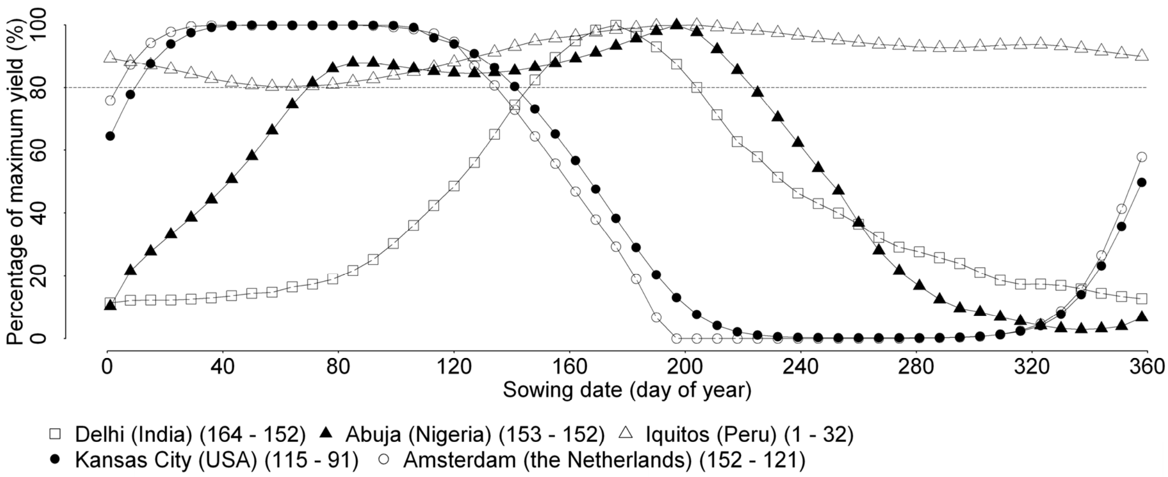

Figure B-1 Sensitivity of maize yield to sowing dates for five locations. Between brackets, the simulated respectively observed sowing dates are given. The dashed line indicates 80% of maximum simulated yield.

The sensitivity of simulated maize yield to the sowing date at a location with no seasonality (Iquitos, Peru) is relatively small: simulated yield is, irrespective of sowing date, always at least 80% of the maximum simulated yield. Larger sensitivity is shown for locations with temperature seasonality (Amsterdam, the Netherlands and Kansas City, USA). In the Netherlands, yields of at least 80% of the maximum yield are simulated, with sowing dates ranging from day of year 14 to day of year 140. In the USA, yields of at least 80% of the maximum yield are simulated, with sowing dates ranging from day of year 21 to day of year 147. In a location with precipitation seasonality and a long wet season (Abuja, Nigeria), the range of sowing dates which results in simulated yields of at least 80% of the maximum is wider in comparison to a location with a shorter wet season (Delhi, India).

C WATER STRESS AFFECTING ROOT BIOMASS

Without water stress, root biomass decreases from 40 % at the beginning of the phenological cycle to a minimum of 20 % of total biomass at maturity (Neitsch *et al.*, 2002) (Figure C-1 A).

$$froot = froot_{max} - frootmin_{min} \times fphu$$

With increasing water stress the fraction of total biomass allocated to the roots now increases exponentially between that minimum and a maximum of 40 % of total biomass (similar to the reduction in the harvest index with increasing water stress described in (Neitsch *et al.*, 2002)) in order to enhance water uptake from an extensive root system during dry periods (Figure C-1 B).

$$froot = (froot_{max} - frootmin_{min} \times fphu) \times \frac{wsf}{wsf + e^{6.13 - 0.00883 \times wdf}}$$

As the above ground biomass thus more strongly responds to water stress, the harvest index is no longer scaled by water stress as originally described by Bondeau *et al.* (2007).

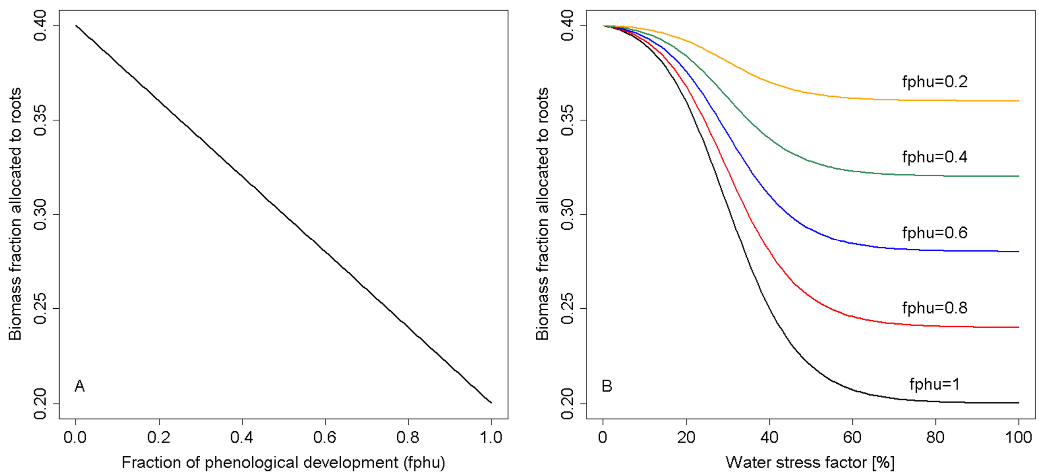

Figure C-1 Biomass fraction allocated to the roots as simulated in LPJmL, A: without water stress as a function of phenological development, and B: depending on the water stress factor at different phenological stages. A water stress factor of 0 indicates high water stress

D COMPARISON OF THE START OF THE GROWING SEASON TO SATELLITE DATA

We compare the start of the main rainy season simulated by LPJmL to the start of the growing season obtained from MODIS satellite data providing the time of greening up (Figure D-1) in order to validate the correct timing of a crop's sowing date.

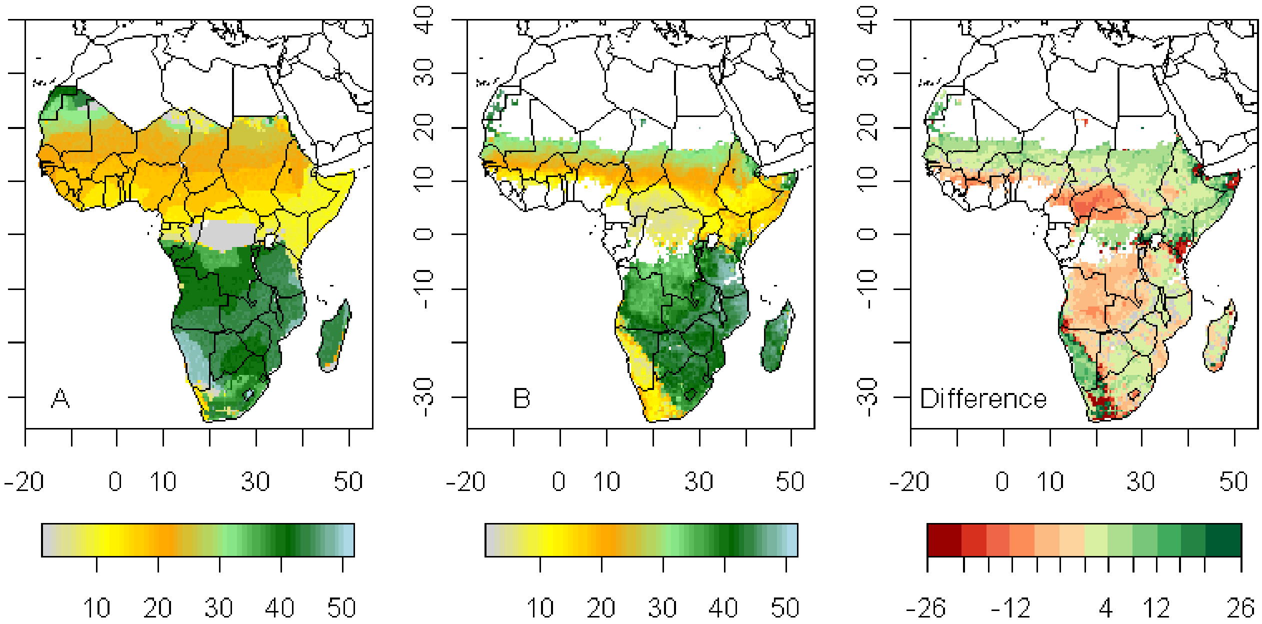

Figure D-1 Comparison of A: simulated and B: observed start of the growing season (in weeks). Simulations were made with LPJmL and the observed start of the growing season is derived from MODIS satellite data (HarvestChoice, 2010). White areas indicate no data.

The differences between the simulated and observed start of the growing season are low with a mean error of 2 ¾ weeks, and a Willmott coefficient of agreement of 0.56. There are considerably larger disagreements than 20 weeks in the mountainous regions of Eastern Africa and desert regions of Namibia.

E MODEL'S ABILITY TO SIMULATE NATIONAL CROP YIELDS IN SUB-SAHARAN AFRICA

To provide an assessment of the validness of crop yields simulated with LPJmL we compare country-averaged yields from six crops used in this study in 48 countries of sub-Saharan Africa for the five-year period from 1999 to 2003 to FAO yields in the same period (FAO, 2011a). The annual fractional coverage of individual crop area per grid cell is prescribed using a newly developed land-use dataset (Fader *et al.*, 2010). As a measure of agreement we calculate the Willmott coefficient of agreement (W) (Willmott, 1982) and the Nash-Sutcliffe efficiency (EF) (Nash & Sutcliffe, 1970) from the area-weighted deviations between simulated and observed yields:

$$W = 1 - \frac{\sum_{i=1}^{N} (S_i - O_i)^2 \times A_i}{\sum_{i=1}^{N} \left(|S_i - \overline{O}| + |O_i - \overline{O}|\right)^2 \times A_i} \qquad EF = 1 - \frac{\sum_{i=1}^{N} (S_i - O_i)^2 \times A_i}{\sum_{i=1}^{N} \left(O_i - \overline{O}\right)^2 \times A_i}$$

where, S_i is the simulated LPJmL and O_i the observed FAO yield (t FM/ha) in a country *i*, $\overline{O}$ the mean observed FAO yield, A_i the cultivated area (ha) of a crop in country *i*, and *N* the number of countries. The Nash-Sutcliffe efficiency ranges from -∞ to 1 (perfect fit), and the Willmott index of agreement ranges from 0 to 1 (perfect fit).

As the rice yield in Somalia of 5.88 t/ha reported from FAO seems to be far too high and is based on unofficial statistics, we used SPAM data (You & Wood, 2004; You *et al.*, 2010), which gives a rice yield of 1.85 t/ha for the year 2000 for comparison to LPJmL rice yield. Figure E-1 to Figure E-6 show the comparison between LPJmL and FAO yields for the six crops simulated in this study.

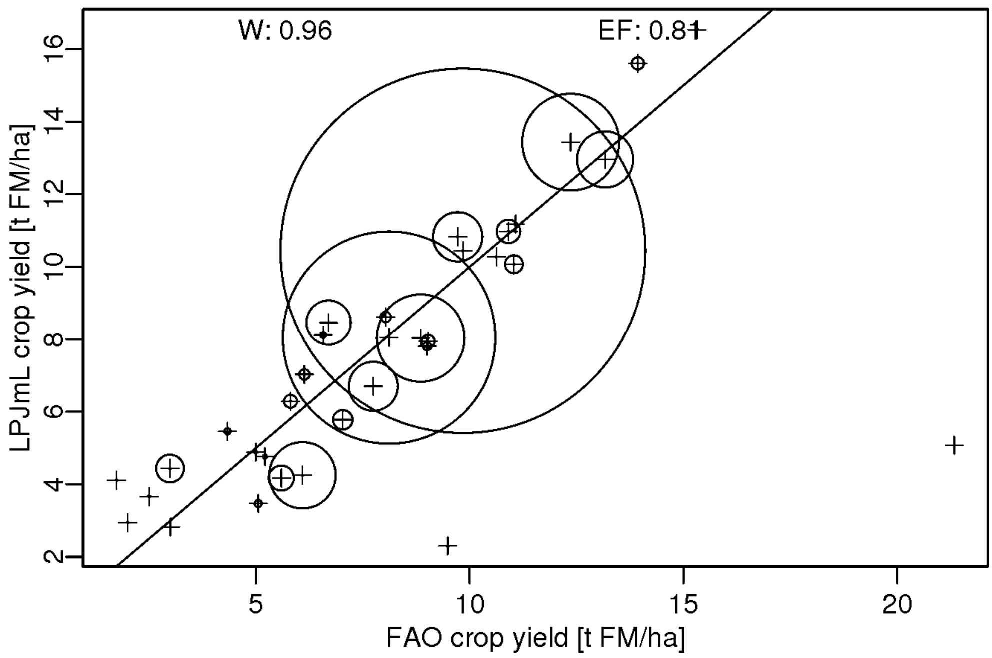

Figure E-1 Comparison of LPJmL and FAO cassava yields. Circle radius indicates the size of total cropland under cassava in an individual country.

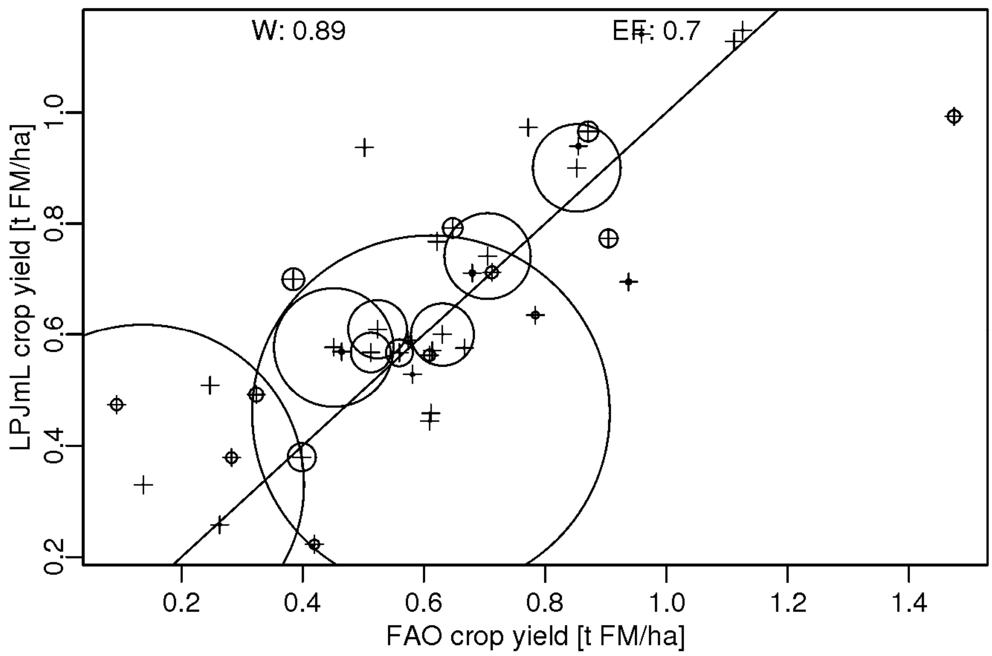

Figure E-2 Comparison of LPJmL and FAO cowpea yields. Circle radius indicates the size of total cropland under cowpea in an individual country.

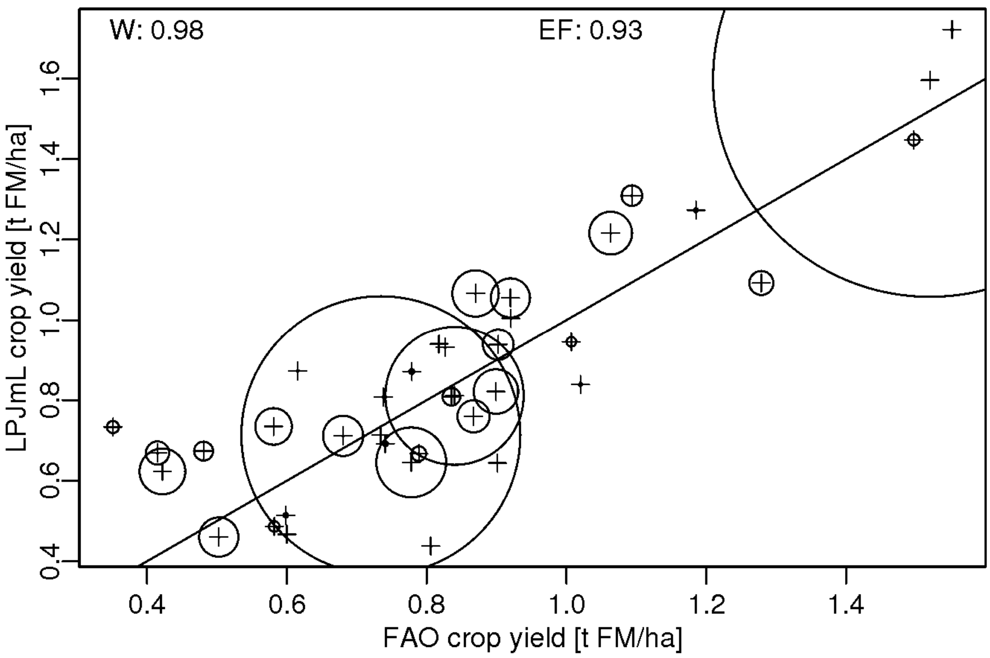

Figure E-3 Comparison of LPJmL and FAO groundnut yields. Circle radius indicates the size of total cropland under groundnut in an individual country.

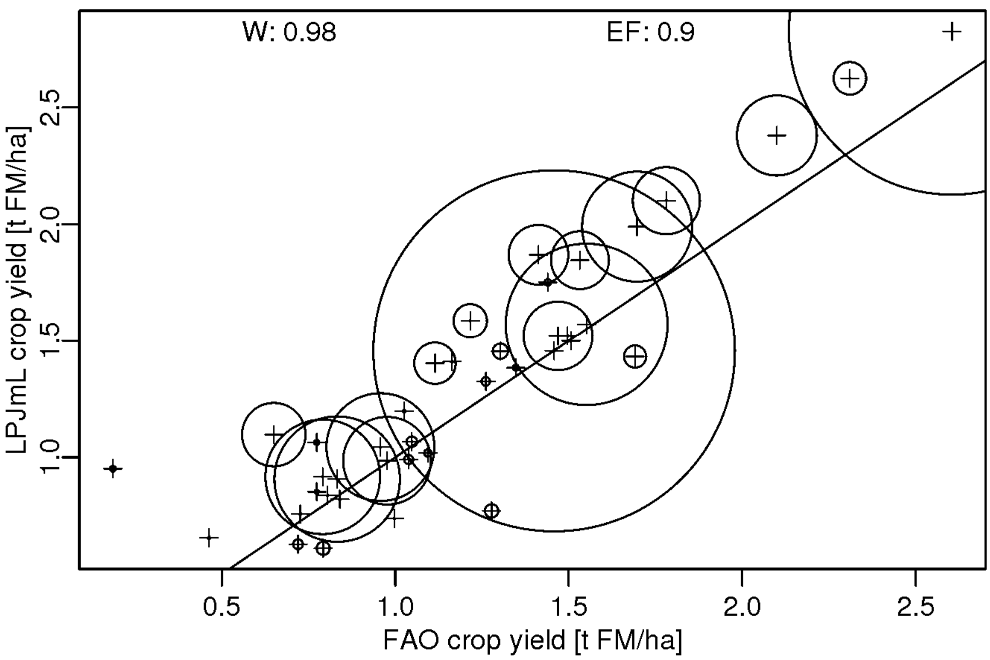

Figure E-4 Comparison of LPJmL and FAO maize yields. Circle radius indicates the size of total cropland under maize in an individual country.

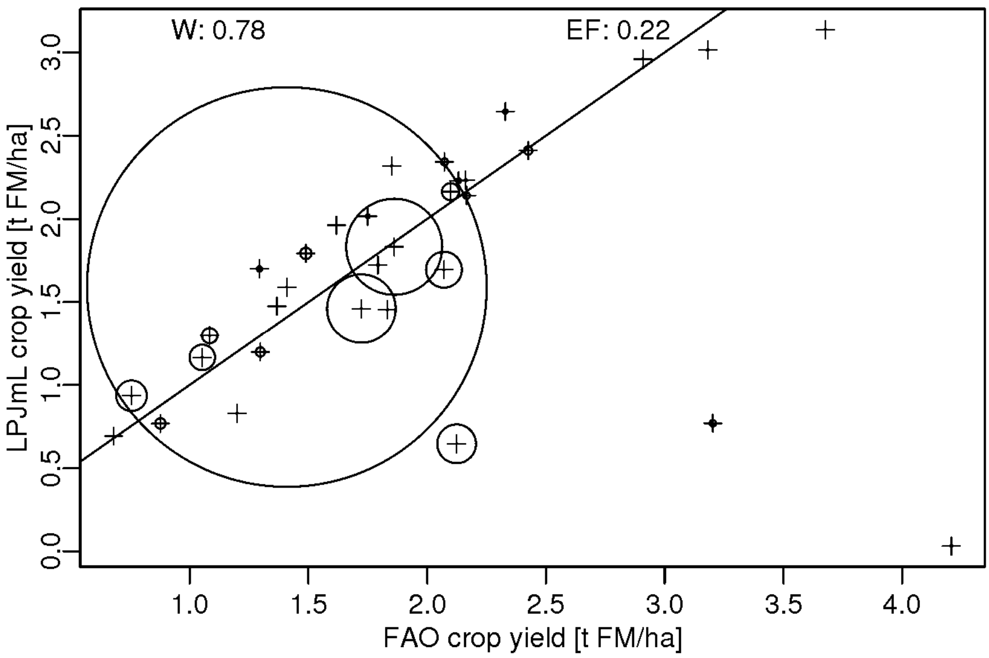

Figure E-5 Comparison of LPJmL and FAO rice yields. Circle radius indicates the size of total cropland under rice in an individual country.

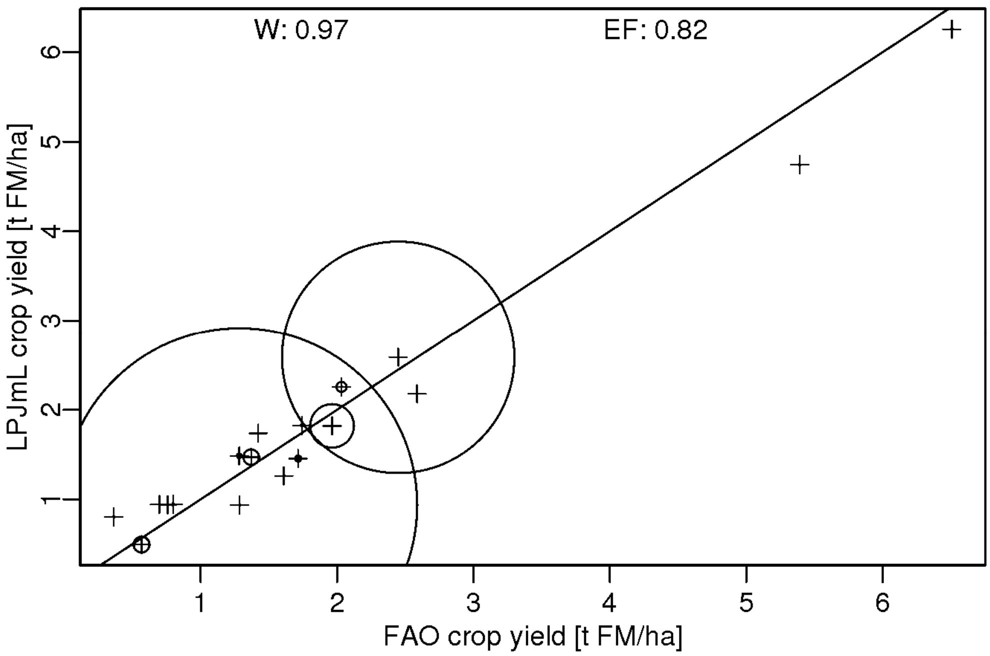

Figure E-6 Comparison of LPJmL and FAO wheat yields. Circle radius indicates the size of total cropland under wheat in an individual country

F DETAILED LIST OF SIMULATED CROP YIELDS PER LOCATION

Table F-1 Overview of mean crop yields and crop yield changes per country and management scenario in 2070-2099 compared to 1971-2000 averaged over three GCMs. Values are mean crop calorific yields in grid cells with a specific combination of a traditional sequential cropping system (TS/TSco) and a highest-yielding sequential cropping system (HS/HSco).

Country and administrative unit		**Crop yield 1971-2000 [Mcal/ha]**						**Crop yield 2070-2099 [Mcal/ha]**					
		TSco	TS	SCco	SC	HSco	HS	TSco	TS	SCco	SC	HSco	HS
Burkina Faso	Bama	Rice-Rice		Rice		Maize-Maize		Rice-Rice		Rice		Maize-Maize	
		13666	18717	11204	10498	13666	18717	12222	12849	4769	4057	12222	12849
								(-11%)	(-31%)	(-57%)	(-61%)	(-11%)	(-31%)
	Tibele	Rice-Maize		Rice		Maize-Maize		Rice-Maize		Rice		Maize-Maize	
		7907	10135	2418	6105	16012	16196	5531	6521	479	2181	10939	12629
								(-30%)	(-36%)	(-80%)	(-64%)	(-32%)	(-22%)
Cameroon	Sanaga Maritime, Wouri	Groundnut-Maize		Groundnut		Wheat-Maize		Groundnut-Maize		Groundnut		Wheat-Maize	
		9668	9633	3218	3189	14247	14093	7989	8136	2360	2502	11475	12003
								(-17%)	(-16%)	(-27%)	(-22%)	(-19%)	(-15%)
	Mbam-et-Inoubou	Maize-Groundnut		Maize		Wheat-Maize		Maize-Groundnut		Maize		Wheat-Maize	
		12210	12239	8671	8701	16388	16484	10090	10176	7757	7616	12947	13841
								(-17%)	(-17%)	(-11%)	(-12%)	(-21%)	(-16%)
	Vina	Maize-Wheat		Maize		Maize-Wheat		Maize-Wheat		Maize		Maize-Wheat	
		18120	19317	10977	11571	18120	19317	16356	17953	8909	9813	16356	17953
								(-10%)	(-7%)	(-19%)	(-15%)	(-10%)	(-7%)
	Moungo, Sanaga-Maritime	Groundnut-Maize		Groundnut		Maize-Wheat		Groundnut-Maize		Groundnut		Maize-Wheat	
		9839	9906	3239	3270	14850	14802	7967	8233	2312	2535	12347	12652
								(-19%)	(-17%)	(-29%)	(-22%)	(-17%)	(-15%)

Continuation Table F-1

Cameroon	Momo	Groundnut-Cassava		Groundnut		Maize-Wheat		Groundnut-Cassava		Groundnut		Maize-Wheat	
		8496	8694	3557	3619	15944	15958	10127 (19%)	8448 (-3%)	2528 (-29%)	2774 (-23%)	13208 (-17%)	13545 (-15%)
	Vina	Maize-Wheat		Maize		Maize-Maize		Maize-Wheat		Maize		Maize-Maize	
		17808	18189	9736	10253	18937	19144	14243 (-20%)	15900 (-13%)	7887 (-19%)	8858 (-14%)	14956 (-21%)	16163 (-16%)
	Various (>3)	Maize-Maize		Maize		Maize-Maize		Maize-Maize		Maize		Maize-Maize	
		16188	16729	9050	9349	16188	16729	13824 (-15%)	14384 (-14%)	7686 (-15%)	8103 (-13%)	13824 (-15%)	14384 (-14%)
	Nyong-et-Kelle	Cassava-Maize		Cassava		Maize-Maize		Cassava-Maize		Cassava		Maize-Maize	
		11352	11355	10788	10984	14382	14193	10886 (-4%)	11650 (3%)	10587 (-2%)	10329 (-6%)	12788 (-11%)	12410 (-13%)
	Lekie	Cassava-Cowpea		Cassava		Maize-Maize		Cassava-Cowpea		Cassava		Maize-Maize	
		11737	11741	10803	10787	14776	14825	11304 (-4%)	10572 (-10%)	10114 (-6%)	10283 (-5%)	12865 (-13%)	12729 (-14%)
	Moungo, Ntem	Groundnut-Maize		Groundnut		Maize-Maize		Groundnut-Maize		Groundnut		Maize-Maize	
		8388	8797	3944	3932	14399	14412	6870 (-18%)	7806 (-11%)	2948 (-25%)	3103 (-21%)	12676 (-12%)	12715 (-12%)
	Mbam-et-Inoubou	Maize-Groundnut		Maize		Maize-Maize		Maize-Groundnut		Maize		Maize-Maize	
		12291	12487	9055	9251	17016	17181	9824 (-20%)	10377 (-17%)	7931 (-12%)	8168 (-12%)	14045 (-17%)	14420 (-16%)
	Bui	Ground.-Ground.		Groundnut		Maize-Maize		Ground.-Ground.		Groundnut		Maize-Maize	
		8263	8290	6501	6529	15094	15223	8301 (0%)	8516 (3%)	4039 (-38%)	4411 (-32%)	17384 (15%)	16852 (11%)
	Manju	Groundnut-Maize		Groundnut		Cassava-Maize		Groundnut-Maize		Groundnut		Cassava-Maize	
		7445	7362	2560	2590	11670	11715	4911 (-34%)	4420 (-40%)	1700 (-34%)	2036 (-21%)	10159 (-13%)	10170 (-13%)

Continuation Table F-1														
Ethiopia	Kembata-Timbaro, Wolaita	Maize-Wheat		Maize		Cassava-Cowpea		Maize-Wheat		Maize		Cassava-Cowpea	
		11659	12490	10212	10942	16854	18755	9542 (-18%)	10958 (-12%)	8214 (-20%)	9321 (-15%)	14539 (-14%)	17797 (-5%)
Ghana	Nkwanta	Maize-Rice		Maize		Cassava-Cowpea		Maize-Rice		Maize		Cassava-Cowpea	
		11840	12033	5554	5814	13458	13645	8155 (-31%)	9452 (-21%)	4329 (-22%)	4915 (-15%)	11524 (-14%)	11904 (-13%)
	Various (>3)	Maize-Maize		Maize		Cassava-Cowpea		Maize-Maize		Maize		Cassava-Cowpea	
		9794	10361	5212	5756	14449	14829	8008 (-18%)	8847 (-15%)	4077 (-22%)	4882 (-15%)	12040 (-17%)	12719 (-14%)
	Tolon-Kumbungu	Groundnut-Rice		Groundnut		Cassava-Cowpea		Groundnut-Rice		Groundnut		Cassava-Cowpea	
		11210	11606	4681	5104	12368	12725	6181 (-45%)	7873 (-32%)	1948 (-58%)	3134 (-39%)	10432 (-16%)	10861 (-15%)
	Sene	Groundnut-Maize		Groundnut		Cassava-Cowpea		Groundnut-Maize		Groundnut		Cassava-Cowpea	
		10755	10328	5361	5243	12882	13536	7551 (-30%)	7575 (-27%)	3334 (-38%)	3398 (-35%)	11310 (-12%)	11840 (-13%)
Kenya	Muranga, Nyeri, Embu	Maize-Maize		Maize		Wheat-Maize		Maize-Maize		Maize		Wheat-Maize	
		4815	4847	5167	5170	10051	10601	8615 (79%)	9614 (98%)	7878 (52%)	8115 (57%)	15968 (59%)	17462 (65%)
	Nyeri	Maize-Maize		Maize		Rice-Rice		Maize-Maize		Maize		Rice-Rice	
		5267	5339	5659	5685	9883	9870	8757 (66%)	9292 (74%)	8147 (44%)	8481 (49%)	15563 (57%)	15945 (62%)
	Kajiado, Kitui	Maize-Maize		Maize		Maize-Maize		Maize-Maize		Maize		Maize-Maize	
		5986	8008	3123	4527	5986	8008	5006 (-16%)	7399 (-8%)	2678 (-14%)	4350 (-4%)	5006 (-16%)	7399 (-8%)
	Various (>3)	Maize-Maize		Maize		Cassava-Maize		Maize-Maize		Maize		Cassava-Maize	
		10038	10959	6325	7144	16262	17009	9929 (-1%)	11398 (4%)	5205 (-18%)	6332 (-11%)	12330 (-24%)	15549 (-9%)

Continuation Table F-1

Kenya	Kakamenga	Maize-Groundnut		Maize		Cassava-Maize		Maize-Groundnut		Maize		Cassava-Maize	
		16128	17086	6753	7546	22401	23206	10850 (-33%)	13313 (-22%)	5436 (-20%)	6780 (-10%)	15162 (-32%)	19433 (-16%)
	Various (>3)	Maize-Maize		Maize		Cassava-Cowpea		Maize-Maize		Maize		Cassava-Cowpea	
		7541	9497	4714	5885	12010	13991	6658 (-12%)	8831 (-7%)	3891 (-17%)	5154 (-12%)	9414 (-22%)	11822 (-15%)
	Bungoma	Maize-Groundnut		Maize		Cassava-Cowpea		Maize-Groundnut		Maize		Cassava-Cowpea	
		9473	9862	9267	9784	27098	28204	16435 (73%)	18003 (83%)	7335 (-21%)	8172 (-16%)	23307 (-14%)	26014 (-8%)
	Various (>3)	Maize-Maize		Maize		Cassava-Cowpea		Maize-Maize		Maize		Cassava-Cowpea	
		5177	7501	4269	5708	7744	9118	4592 (-11%)	7497 (0%)	3544 (-17%)	5049 (-12%)	3494 (-55%)	7026 (-23%)
	Bomet	Maize-Maize		Maize		Ground..-Ground.		Maize-Maize		Maize		Ground..-Ground.	
		9666	9676	10376	10388	19512	19586	15287 (58%)	14988 (55%)	8776 (-15%)	8922 (-14%)	18422 (-6%)	16283 (-17%)
South Africa	Bethlehem, Lydenburg	Wheat-Maize		Wheat		Wheat-Maize		Wheat-Maize		Wheat		Wheat-Maize	
		15923	15888	12742	12831	15923	15888	15268 (-4%)	16875 (6%)	7110 (-44%)	9341 (-27%)	15268 (-4%)	16875 (6%)
	Aberden	Maize-Wheat		Maize		Wheat-Maize		Maize-Wheat		Maize		Wheat-Maize	
		3446	3495	3664	3705	10581	10396	3961 (15%)	4974 (42%)	2550 (-30%)	4417 (19%)	7011 (-34%)	3555 (-66%)
	Lydenburg	Wheat-Maize		Wheat		Maize-Wheat		Wheat-Maize		Wheat		Maize-Wheat	
		8985	9802	8541	8283	15620	15660	14090 (57%)	21531 (120%)	3617 (-58%)	13177 (59%)	17318 (11%)	19634 (25%)
	Aberden	Maize-Wheat		Maize		Cassava-Maize		Maize-Wheat		Maize		Cassava-Maize	
		3978	3922	4300	4234	4199	4155	3792 (-5%)	3556 (-9%)	3839 (-11%)	3054 (-28%)	3872 (-8%)	3900 (-6%)
	Aberden	Maize-Wheat		Maize		Cassava-Cowpea		Maize-Wheat		Maize		Cassava-Cowpea	
		4827	4898	5124	4964	4900	5129	4987 (3%)	4732 (-3%)	4580 (-11%)	3847 (-22%)	706 (-86%)	2703 (-47%)

Continuation Table F-1														
Zimbabwe	Masvingo	Maize-Wheat		Maize		Maize-Wheat		Maize-Wheat		Maize		Maize-Wheat	
		13063	12505	4160	4179	15299	15931	9130 (-30%)	11357 (-9%)	1542 (-63%)	3082 (-26%)	3954 (-74%)	9161 (-42%)
	Chegutu, Chipinge	Maize-Maize		Maize		Maize-Maize		Maize-Maize		Maize		Maize-Maize	
		6042	7091	2966	3840	9791	14778	4256 (-30%)	5632 (-21%)	1527 (-49%)	2763 (-28%)	3857 (-61%)	8347 (-44%)

G GLOBAL CIRCULATION MODELS USED IN THIS STUDY

Table G-1 Global circulation models used in this study (Randall *et al.*, 2007).

Model name	Research Group(s)	Country	Available reporting periods
CGCM3.1(T47)	Canadian Centre for Climate Modelling and Analysis	Canada	2046-2065, 2081-2100
CNRM-CM3	Météo-France / Centre National de Recherches Météorologiques	France	2046-2065, 2081-2100
CSIRO-Mk3.0	Commonwealth Scientific and Industrial Research Organisation, Atmospheric Research	Australia	2046-2065, 2081-2100
ECHAM5/MPI-OM	Max Planck Institute for Meteorology	Germany	2046-2065, 2081-2100
GFDL-CM2.0	U.S. Department of Commerce / National Oceanic and Atmospheric Administration / Geophysical Fluid Dynamics Laboratory	USA	2046-2065, 2081-2100
GFDL-CM2.1			2046-2065, 2081-2100
IPSL-CM4	Institut Pierre Simon Laplace	France	2046-2065, 2081-2100
MRI-CGCM2.3.2	Meteorological Research Institute	Japan	2046-2065, 2081-2100
PCM	National Center for Atmospheric Research	USA	2046-2065, 2080-2099

The Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset contains more than these GCMs. For this study eight GCMs were excluded because the data was not complete and one GCM was excluded because data on the precipitation amount in the wet season deviates from the mean by more than three standard deviations.

H METHOD OF GENERATING STYLIZED PRECIPITATION SCENARIOS

Identifying the largest change in wet season characteristics

We first calculate the largest relative changes in total precipitation and length of the wet season in combination for each grid cell after excluding all outliers that deviate from the mean by more than two standard deviations to avoid overly emphasizing on extremes. We do this for the two time periods 2060s and 2085s separately as follows:

$$\min\left(\frac{P_{i,t}-P_{i,1995}}{P_{i,1995}}+\frac{L_{i,t}-L_{i,1995}}{L_{i,1995}}\right) \quad \forall \quad i=1,...,9$$

with n=9, where $P_{i,t}$ and $L_{i,t}$ are the precipitation in the wet season and length of the wet season, respectively at time t and for GCM i, $P_{i,1995}$ and $L_{i,1995}$ the precipitation in the wet season and length of the wet season in the 1995s and for GCM i.

We then assign the individual relative changes in both variables to the baseline climate of the WATCH Forcing Data (WFD) to obtain the daily precipitation for the climate experiments Cp, Cl and CpClCt described in the methods section. Figure H-1 shows an example for changes in daily precipitation in the 2060s for the GCM ECHAM5.

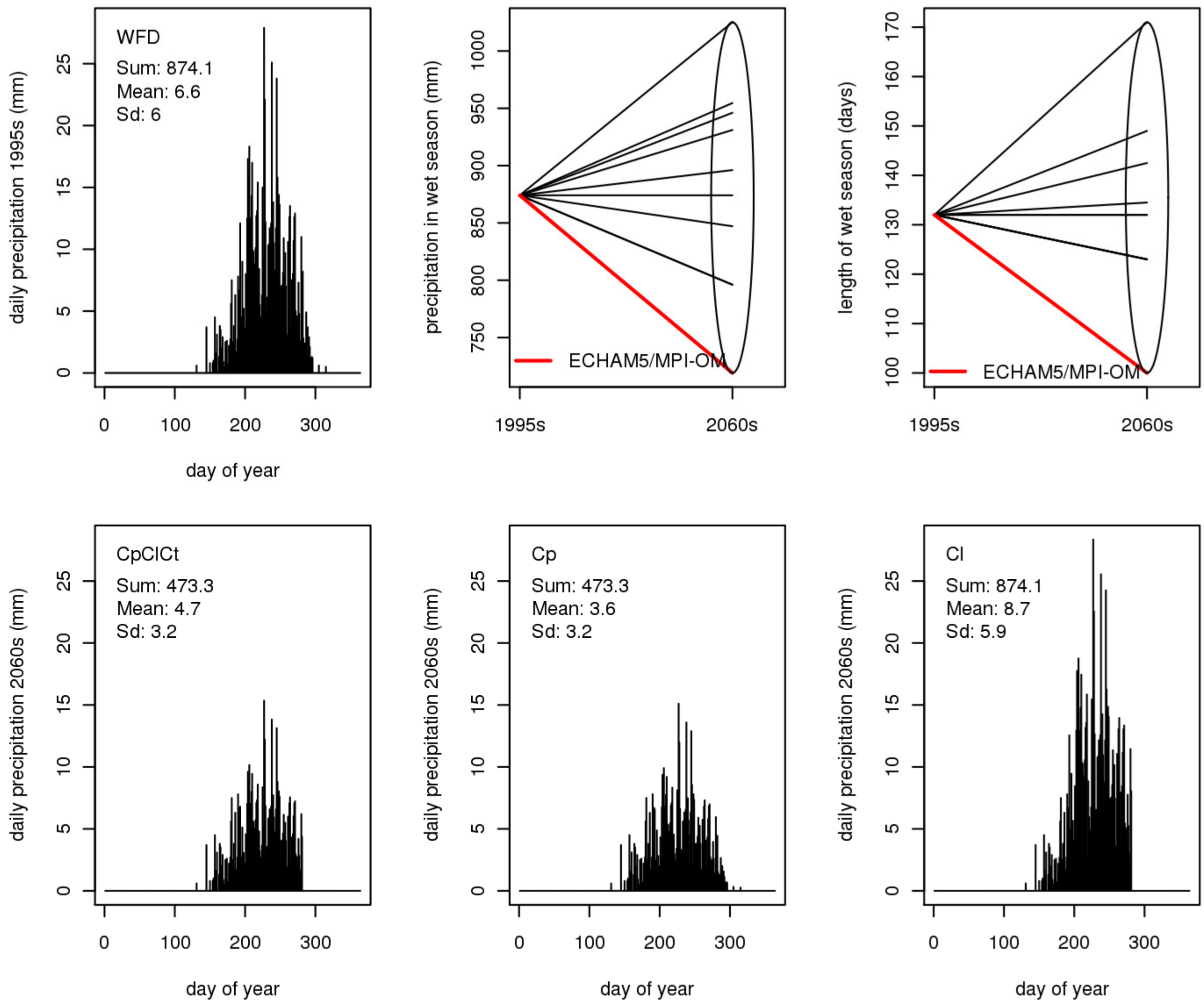

Figure H-1 Daily precipitation changes in the 2060s for an example cell (Gambia: Lat = 13° 25' N, Lon = 16° 75' W). Top: Daily precipitation in the 1995s from WATCH Forcing Data (WFD) and projected changes in total precipitation and length of the wet season from nine GCMs. Bottom: Daily precipitation in the 2060s in the three climate experiments CpClCt (combined), Cp (Changed precipitation), and Cl (Changed length).

Overestimation of precipitation changes

It is assumed that assigning relative changes from GCM data to WATCH Forcing Data (WFD) as a common baseline climate is an adequate procedure, as this data lies within the range of baseline climates from all GCMs (Figure H-1). However, the Kolmogorov–Smirnov test on the equality of distributions indicates that the total precipitation and the length of the wet season in the 1995s calculated from GCMs and from WFD differ significantly ($p<0.001$) (Figure H-1). Therefore, changes in the

2060s and the 2085s in total precipitation and length of the wet season may be overestimated if GCMs significantly underestimate actual values (Füssel, 2003).

The test statistic of the Kolmogorov-Smirnov test D gives an indication of the direction and strength of these differences. D is the maximum vertical deviation between two cumulative distribution functions, i.e. for the comparison between WFD and the GCM ECHAM5 with D=0.11, the precipitation amount in the wet season is below ~1800 mm in ~98 % of all grid cells in the GCM but only in ~87 % of all grid cells in WFD (Figure H-1, bottom panel right). ECHAM5 therefore significantly underestimates the precipitation amount in the wet season, just like three other GCMs in which D ranges from 0.08 to 0.33. Furthermore, seven out of nine GCMs always significantly underestimate the length of the wet season (Figure H-1, bottom panel left, curves above WFD curve), with D ranging from 0.18 to 0.36. However, the quality of agreement to WFD varies regionally for all GCMs, e.g. the GCM GFDL-CM2.1 underestimates the precipitation amount in the wet season lower than 1000 mm but overestimates precipitation amounts between 1000 mm and 2000 mm (Figure H-1, panel top right).

However, we assume that the risk to extremely under- or overestimate the wet season length and precipitation in the future is reduced by removing GCMs as outliers if they deviate from the mean by more than two standard deviations.

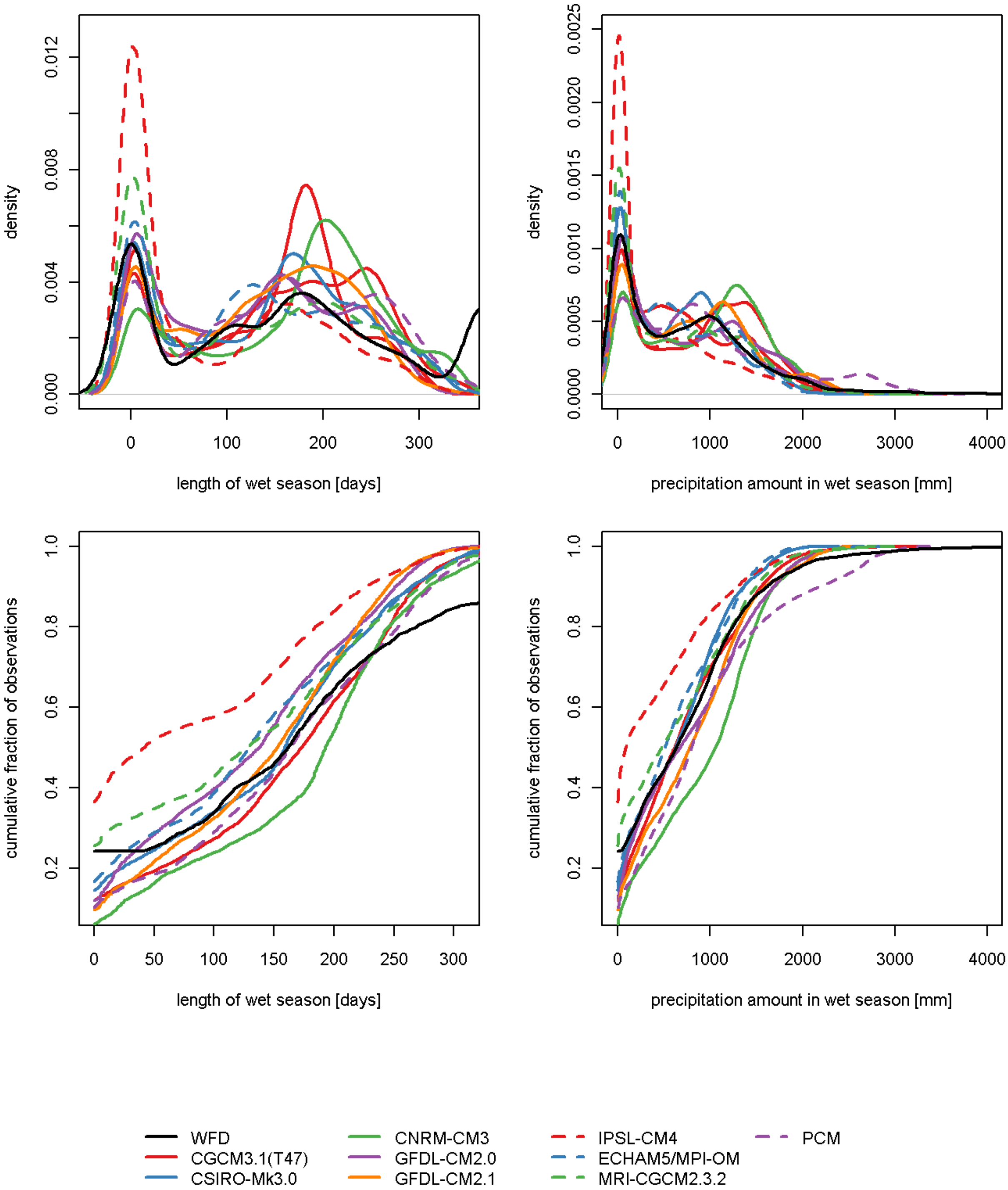

Figure H-1 Distribution function (top) and cumulative distribution function (bottom) of the length of the wet season (left) and the precipitation amount in the wet season (right) in the baseline climate calculated from the WATCH Forcing Data (WFD) and from nine GCMs.

I METHOD FOR CALCULATING CROP YIELD AND CROP YIELD CHANGES

The combined (ΔYI_{CpClCt}) and separated effects of temperature, length of rainy season and total precipitation in the rainy season (ΔYI_{Ct} , ΔYI_{Cl} and ΔYI_{Cp}) on crop yield in each grid cell for two time periods are calculated as follows:

$$\Delta YI_{CpClCt} = \frac{YI[P_t, L_t, T_t] - YI[P_{95}, L_{95}, T_{95}]}{YI[P_{95}, L_{95}, T_{95}]}$$

$$\Delta YI_{Cp} = \frac{YI[P_t, L_{95}, T_{95}] - YI[P_{95}, L_{95}, T_{95}]}{YI[P_{95}, L_{95}, T_{95}]}$$

$$\Delta YI_{Cl} = \frac{YI[P_{95}, L_t, T_{95}] - YI[P_{95}, L_{95}, T_{95}]}{YI[P_{95}, L_{95}, T_{95}]}$$

$$\Delta YI_{Ct} = \frac{YI[P_{95}, L_{95}, T_t] - YI[P_{95}, L_{95}, T_{95}]}{YI[P_{95}, L_{95}, T_{95}]}$$

where $YI[P_{95}, L_{95}, T_{95}]$ is the maize yield under precipitation (total precipitation in rainy season and length of rainy season) and temperature conditions kept constant at the 1995s level, $YI[P_t, L_t, T_t]$ the maize yield if the precipitation (total precipitation in rainy season and length of rainy season) and temperature conditions change over time (t is the 10-years period 2060s or the 2085s), $YI[P_t, L_{95}, T_{95}]$, $YI[P_{95}, L_t, T_{95}]$, $YI[P_{95}, L_{95}, T_t]$ the maize yield under changed total precipitation in the rainy season, changed length of the rainy season and increased temperature, respectively.

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