SIMULATION OF CROP YIELDS IN THE AMHARA REGION USING A LARGE AREA CROP MODEL AS DRIVEN BY OUTPUT FROM REGCM-4

By:

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Dedicated to for those family and friends of mine who have unlimited potential but can not attend this school.

Abstract

The livelihood of people in many regions of Ethiopia depends on rainfed agriculture. Accurate prediction of crop yield could greatly improve potential famine and allow advanced planning of intervention operations. This thesis explores the feasibility of a combined Regional Climate Model (RegCM) and crop model for crop yield forecasting in Ethiopia, using wheat yield for the Amhara region as a case study. An important focus in the investigation is to validate and asses the ability of RegCM-4 regional climate model to represent the Ethiopian summer rainfall. The ability of the RegCM-4 model in capturing temporal and spatial variability of precipitation over the region of interest is evaluated using metrics spanning a wide range of temporal and spatial (Ethiopian domain average to local) scales against Global Precipitation Climatology Project (GPCP) observational datasets. The simulated period is 1995-2008. RegCM-4 shows a general overestimation of precipitation except the highlands part of the country. The precipitation bias over the Ethiopian highland, our main area of interest, is mostly less than 20%. The model captures well the observed interannual and inter-seasonal variability. On short time scales, simulated daily temperature and precipitation show a high correlation with observations, with a correlation coefficient of 0.79 for kiremit season. It is therefore that RegCM-4 has sufficiently good quality to perform climate change experiments over Ethiopia, for application to impact and adaptation studies. RegCM-4 outputs are used to drive a process-based crop model, General Large Area Model for Annaula Crop (GLAM) for hindcasting zonal wheat yields in the Amhara region. Simulated crop Radiation Use Efficiency (RUE) has been founded to be 1.81 which is expected for C_3 crops. The yield in these simulations showed a negative bias (159-200kg/ha) with observed yield over Souther(North Shew Zone) and South Western(Awi Zone) of Amhara regional state. This is probably because at the field level the yield variability was mainly affected by field managements and diseases, pests and so on. GLAM does not predict the effect of the detailed field management, diseases and pests on yield variability; and also in this region there is overestimation of RegCM-4 precipitation, which might have lead to water stress in GLAM model. At regional level(for all grid cells), there were higher correlations (0.74) between observed and simulated yield. We therefore conclude that the GLAM model is suitable to simulate crop yield at regional scale (approximately 50 km) using RegCM-4 outputs.

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Nomenclature

C_{YG}	yield gap parameter
e_{sat}	saturated vapor pressure
E	evaporation
E_T	normalised transpiration efficiency
$E_{TN,max}$	maximum transpiration efficiency
Ee	'Energy-limited' evaporation
Es_{POT}	soil-structure limited potential evaporation
H_I	harvest index
l_v	volumetric root length density
L	leaf area index
Q	incoming water flux
R	runoff
R_N	net all-wave radiation
S	soil stress factor
t	time
t_e	time of arrival of extraction root front
t_R	time since first rain
t_{TT}	thermal time
T	air temperature
$\bar{T}$	average daily air temperature
T_b	base cardinal temperature

T_m	maximum cardinal temperature
T_o	optimum cardinal temperature
T_{eff}	effective temperature
TT	transpiration
TT_{pot}	potential transpiration
T_Te	energy-limited transpiration
TT_p	physiologically-limited transpiration
v_{EF}	extraction front velocity
V	vapor pressure deficit
W	above-ground biomass
Y	yield
z	depth of soil from surface
z_{max}	maximum soil depth
Z	rainfall
α	Priestly-Taylor coefficient
γ	psychometric constant
λ	latent heat of vaporisation of water
θ	soil water content
θ_{dll}	drained-lower limit
θ_{dul}	drained-upper limit
θ_{sat}	saturation limit
θ_{pe}	potentially extractable water
$(\frac{\partial L}{\partial t})_{max}$	maximum rate of LAI increase

List of Acronyms

BATS	Biosphere-Atmosphere Transfer Scheme
CCM3	Community Climate Model Version-2
CSA	Central Statics Agency
CV	Coffiecient of Variations
ECMWF	European Centre for Medium-Range Weather Forecasts
ET	Evapotranspiration
Eto	Evaporative Demand
FAO	Food and Agriculture Organization of the United Nations
GCM	General Circulation Model
GLAM	General Large Area Model for Annaula Crop
GPCP	Global Precipitation Climatology Project
GTOPO30	Global 30 arc second elevation dataset
HI	Harvest Index
ICTP	Abdus Salam International Centre for Theoretical Physics
ICTZ	Inter Tropical Convergence Zone
IPCC	Intergovernmental Panel on Climate Change
MM5	Mesoscale Model version 5
NCAR	National Center for Atmospheric Research
NOAA	National Oceanic and atmospheric Administration
OISST	Optimum Interpolation Sea Surface Temprature
RCM	Regional Climate Model
RegCM4	REGional Climate Model version 4
RMSE	Root Mean Square Error
SLA	Specific Leaf Area
SST	Sea Surface Temperature
USGS	United States Geological Survey
VPD	Vapor Presure Diflict
YGP	Yield Gap Parametre

Chapter 1

Introduction

Crop simulation model is a representation of a simplified crop production system, and it consists of non-linear mathematical equations and logic to provide a systematic analysis of the crop production system (Ritchie, 1991). Models of this type take into account underlying physiological processes of crop growth; they operate on a range of temporal resolutions: monthly, daily or even hourly time-step. They have been developed with different levels of biological details (Thornton et al., 1997) and run for different environmental conditions such as soil type, weather and management to simulate dynamic processes of crop growth and development. Yet, even the most physiologically-based crop models contain empirical relationships (e.g. growing degree-days to simulate phenology) subject to constraints imposed by the range of data observations from which the relationships were inductively or deductively derived.

Research efforts over recent years have taken advantage of increases in computational power and climate/ weather model skill in order to couple climate and impact models. Studies span a range of impacts (crop productivity, e.g., Mearns et al. (1999, 2001); health, e.g. Hoshen et al. (2003); hydrology, e.g., Davis et al. (2003)). Climate has a strong influence on agriculture which is considered the most weather-dependent of all human activities (Oram, 1989). Improved climate prediction therefore offers interesting potential benefits to agriculture. On the one hand, numerous studies have tried to link seasonal prediction outputs from global climate models (GCMs) to crop models, thus translating climate forecasts into seasonal crop predictions Hansen et al. (2006). On the other hand, combining GCMs and crop models also provides a tool to assess the impacts of future climate change on crop production (Jones and Thoronton, 2003). This is particularly important for Sub-Saharan Africa where climate variability and drought threaten food security. However, translating GCM outputs into crop yields is difficult because GCM grid boxes are of larger scale than the processes governing yield, involving partitioning of rain among runoff, evaporation, transpiration, drainage and storage at plot scale (Baron et al., 2005). Integrated climate-crop modeling systems, therefore, need to handle appropriately the loss of variability caused by the difference between scales. This can potentially be achieved by downscaling GCM outputs by various dynamical, empirical or statistic-dynamic methods (Von Storch, 1995). Since impact studies ultimately rely on the accuracy of climate input data (Berg et al., 2010), it is therefore crucial to quantify the errors inevitably propagated by such downscaling techniques through the combined climate/crop modeling (Challinor et al., 2005c).

In addition to the weather data which is an input to the model, there are many sources of error that contribute to disagreement between observed and modeled yields ((Hansen and Jones, 2000)). No crop model formulation is a complete description of the crop and its interaction with the environment. Model parameterizations are simplifications of crop processes that inevitably result in some error. Any yield data will also have associated error, and the necessary separation of the time series into underlying technology trends (defined as a monotonic increase in yield over time due to non-climatic factors, such as improved yield varieties and an increased use of fertilizer) and interannual variability also adds uncertainty. Input of management data, such as planting date, plant population density, and crop variety, have associated uncertainties that will impact the ability of the model to reproduce reality (i.e., model skill). Aggregation error due to the large spatial scale on which the model is run will also contribute to errors in simulated yield. Finally, the input soil and crop data will have inaccuracies. All of these sources of error will limit the accuracy with which yields can be simulated.

The nonlinear response of crops to climate means that changes over time in the relationship between yield and climate (i.e., nonstationarity) may be observed. For example, changes in the fraction of crop under irrigation, or in cultivar-specific properties, such as sensitivity to water stress or pests, could change the response of a crop to the climate. Assumptions regarding the yield technology trend and the planting window (the period of time from which a planting day is chosen) will have direct implications for the observation of any changes, as will any changes over time in the accuracy of the data used. However, trends in yield may also be attributed to trends in climate (Pathak et al., 2003). As well as the impact of seasonal mean climate, the impact of subseasonal weather variability on crop yields can be significant (Gadgil et al., 2002, Hansen and Jones, 2000). Our understanding of the crop-climate system will depend upon the extent to which climatic and non-climatic effects can be separated. The prospects for yield prediction, particularly in the context of climate change, rely, in part, on this understanding. It is for this reason that General Large Area Crop Model(GLAM) is used in this study; it is process based, rather than empirical, and does not rely upon the assumption of stationary yield-weather statistics. It is also designed to simulate the impact of weather on yields, and it can operate on the spatial scales of the reanalysis data.

The general objective of this study is to asses the capability of RegCM4 output together with a large area crop model,to simulate wheat yield.

We perform simulation of wheat yield over Amhara region for two fold purpose: asses the ability of RegCM4 simulation for summer season to produce a key climate factor for crop production by comparing the climate model output and observation and use regional model outputs to drive a crop model and assess the accuracy of simulated yield prediction compared to observation (the observed detrended yield).

This thesis is organized as follows. Following the introductory Chapter 1, a more extensive review of current knowledge on crop-climate interactions, GLAM model description and wheat production area in Ethiopia are explored (Chapter 2). Chapter 3 present a validation analysis of a recent past climate simulation over the Ethiopia with the ICTP (Abdus Salam International Centre for Theoretical Physics) RegCM-4. As mentioned, the model is run at 50 km grid spacing. Using the divisional wheat yield for the Amhara region as case study, Chapter 4 attempts to answer the two questions posed earlier that motivate the present investigation namely, 1) the feasibility of using RegCM-4 outputs for crop yield prediction, 2) crop model yield response to uncertainties in RegCM-4 rainfall simulation. The main features of the GLAM model is presented first, followed by a discussion on the calibration of the crop model for the case of Amhara regional state wheat yield. In Chapter 5, the results of the multiyear RegCM-4 and GLAM simulations of regional rainfall and wheat yield are discussed. Finally, Chapter 6 concludes the thesis with a summary of the main results and the outstanding issues the emerged from the various studies undertaken in previous chapters.

Chapter 2

Scientific Background

2.1 General

The investigation of the interaction of crops and climate is a new area of research in meteorology where the role of vegetation in the climate has only just gained widespread acceptance. Crop scientists generally view the climate as a non-interactive boundary condition. The growth and development of crops is highly dependent on the weather, especially under rainfed conditions in the seasonally arid tropics. Because of the importance of crop production for society, these relationships have been studied extensively. The dependency on weather also means that the distribution of crop species is dependent on the distribution of climate. Crops differ from most other vegetation types in that human intervention controls the type of crop grown, the timings of cultivation and how this may change under future climates. The dynamics of crop growth in response to weather are of a shorter timescale to that of other vegetation types, such as natural grasslands which exhibit much smoother seasonal variations in phenology.

This chapter gives extensive review to identify the key aspects of crop-climate relationships relevant to the work in the subsequent chapters. Firstly, how weather and climate affect crop cultivation will be explored. Secondly, current understanding of how vegetation influences climate will be reviewed, which will necessarily include an examination of how vegetation is represented in climate models. Current climate modelling efforts in which vegetation coverage can respond to variations in climate will also be reviewed before the objectives of this thesis are outlined.

2.2 Climate effects on crops

2.2.1 Overview

The primary process behind crop growth is photosynthesis, which requires the capture of solar radiation by the crop canopy and a supply of CO_2 and water (Hay and Walker, 1989). The passage of weather systems alters, in a matter of minutes, the levels of radiation, temperature and humidity the crop experiences. High frequency variability in precipitation is experienced as filtered slower variations of soil moisture. The diurnal cycle controls the levels of solar energy and temperature while on the longer timescale, the transition of the seasons results most commonly in changes in daily mean temperature and irradiance and, in some regions, rainfall.

The relationship between the seasonal evolution of temperature and precipitation determines the suitable periods for crop cultivation (Bunting, 1974). In the humid tropics warm temperatures and consistent rainfall allow multiple harvests of a crop in a year. In such scenarios, however, high rainfall may be detrimental to crop growth as it may lead to leaching of essential nutrients from the soil. Away from the equator, the temporal distribution of rainfall becomes more seasonally varying. The timing of crop cultivation is highly dependent on the arrival and duration of the rains which are determined by monsoonal air flows driven by land-sea temperature contrasts caused by the heating of the sun. Often production is limited to one crop each year but, if sufficient rains fall, a second crop may be grown, most likely with the aid of irrigation. At higher latitudes the seasonal cycle of temperature increases in amplitude while the distribution of rainfall can vary between regions. At temperate latitudes crop growing seasons are controlled more by temperature than rainfall. The large variation in climate across the globe has resulted in the evolution and breeding of many crop species varying in morphology and physiology, e.g. biennials and perennials. This thesis is primarily

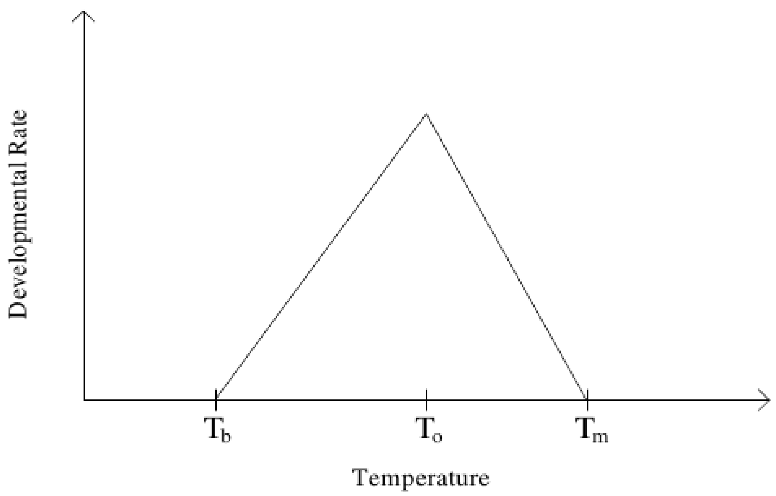

Figure 2.1: Example of the typically observed relationship between rate of crop development and temperature.

concerned with the interaction of annual crops grown in the tropics where crop production is highly dependent on climate and the access to technology to mitigate climatic variations is low. Therefore, the rest of this section is confined to annual crops.

2.2.2 Temperature

The developmental rate of a crop from emergence through to maturity is controlled by temperature. The relationship is non-linear as illustrated by Fig. 2.1. The developmental rate (reciprocal of duration) increases approximately linearly with temperature between the base temperature, T_b, and the optimum, T_o . Once the temperature exceeds the optimum, development slows with increasing temperature up to the maximum temperature, T_m , above which there is no development.

The cardinal temperatures (T_b ,T_o ,T_m) are determined experimentally and vary between crops, cultivars and sometimes between developmental stages of the same crop. The relationship in Fig. 2.1 is used to calculate the thermal time (units of ^{o}C days) for crop phenological development. Certain crops have developed timing mechanisms that respond to the environment. The development from one stage to another, most commonly from vegetative growth to flower initiation, is sometimes sensitive to the length of day (Roberts and Summerfield, 1987). This response, termed photoperiodism, can either require lengthening days (for long day plants) or shortening days (short day plants) and is not always dependent on the passing of an absolute day length threshold. Some crop cultivars are insensitive to day length and are termed day neutral. The response is controlled by the phytochrome pigments in the leaves which actually measure the duration of the night. In general, crops adapted to the tropics are day neutral or require shortening days, while crops from higher latitudes are either long day or day neutral plants.

High temperatures can have detrimental effects on yield for certain crops by causing the abortion of yield forming organs. The possibility of such an effect has been known for a while. Downes (1972) discovered that high temperatures during the germination to initiation period of sorghum had an adverse effect on yield. More recently, the effects of high temperature episodes on rice (Matsui and Horie, 1992), groundnut (Vara Prasad et al., 2000) and wheat (Ferris et al., 1998) have been examined, motivated by the possibility that temperature thresholds will be more frequently breached under climate change (Wheeler et al., 2000). This would make the crop response to climate change non-linear. Fig. 2.2 shows one such response for groundnut. The study of Vara Prasad et al. (2000) also shows that high temperatures in the morning, not the afternoon, result in reduced fruit set.

2.2.3 Carbon dioxide and water

The growth of a crop requires the fixation of carbon from atmospheric CO_2 during photosynthesis (Loomis and Connor, 1992). CO_2 moves down a diffusion gradient from high ambient atmospheric conditions, through stomata, to lower internal leaf concentrations. A side-effect of open stomata is that water vapour is lost from the leaf down a gradient from almost saturated conditions inside the leaf to relatively dry atmospheric air. Therefore, to grow a crop necessarily requires a large volume of water to be transpired. The availability of water to the crop, dependent on the input of precipitation, soil water holding properties and the distribution of roots, is crucial for successful crop cultivation. In many regions water is already, or will become, a scarce quantity (Vorosmarty et al., 2000). Fig. 2.2 shows that by the year 2025, as much as two-thirds of the world population may be subject to moderate to high water stress.

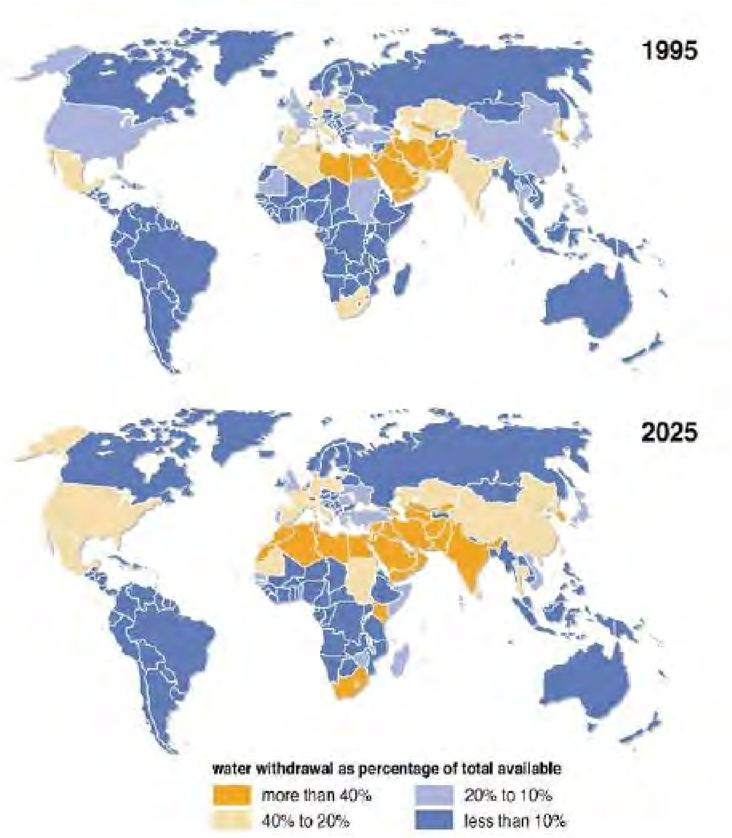

Figure 2.2: Global water stress in 1995 and 2025. Source: WMO and others 1996.

Therefore, the ability to grow crops with less water will remain an active area of research for many years. Much work is concerned with increasing the water use efficiency (WUE) of crops. When WUE is defined as the ratio of accumulated biomass to water lost by evapotranspiration, large improvements can be made by reducing the amount of water that is lost direct from the soil surface by increasing the coverage of the crop faster (Ogola et al., 2002) or using mulches (Kaushik and Lal, 1997). However, when WUE is more strictly defined as the ratio of biomass accumulated to water lost by crop transpiration alone (also termed transpiration efficiency, TE), improvements are harder to achieve. It has been found that WUE is dependent on the climate, especially humidity. Tanner and Sinclair (1983) showed that variations in water requirement of crops could be explained by the variations in humidity as defined by the vapour pressure deficit. Generally, when transpiration is restricted by high humidity, crops accumulate biomass faster (Monteith, 1993).

The actual physiological mechanisms for this, however, remain unclear. It is conceivable that the role of stomata in regulating leaf gas exchange is important. It is known that stomata respond to changes in atmospheric humidity and it is generally accepted that under conditions of low atmospheric humidity they close. The response of stomata could be determined by feedback or feedforward control (Schulze, 1986). Under feedback control, stomata would respond to changes in leaf transpiration in such a way as to minimise further decreases in leaf water potential. Consequently, leaf transpiration would asymptote with increasing evaporative demand. Under feedforward control, leaf epidermal water status would determine stomatal aperture, independent of transpiration. If this were the case then transpiration would increase with evaporative demand up to a point and then decrease. The experimental evidence of Monteith (1995) and, Mott and Parkhurst (1991) suggest that stomata do not respond to either humidity or the leaf to air water vapour deficit, but to the rate of transpiration, thus supporting the feedback control.

A midday depression in CO_2 uptake of plants is commonly observed. If stomatal closure, in response to the low atmospheric humidity, was the mechanism behind this then the supply of CO_2 to the leaf would be reduced. However, it has been found that leaf internal CO_2 concentrations are relatively unaffected by stomatal closure (Zhang and Nobel, 1996) under low atmospheric humidity conditions. This implies that the biochemical properties of the photosynthetic apparatus have also changed. The observed relationship between WUE and conditions of low atmospheric humidity could therefore be due to a greater loss of water concurrent with an unaltered supply of CO_2 for photosynthesis.

When grown under increased ambient CO_2 concentrations, crop yields increase (Matthews et al., 1997), known as the CO_2 fertilisation effect. Stomatal resistance increases under high CO_2 conditions so, therefore, water loss should be minimised. It is difficult to quantify the overall effect potential greenhouse gas induced climate change might have on crop growth and productivity, however, due to the many varied environmental controls on crop growth and the uncertainty associated with climate change predictions.

2.2.4 Crop modelling

Crop models, defined by Sinclair and Seligman (1996) as dynamic representations of crop processes in a system context, can be of value in determining the possible response of crops in many scenarios. Crop modelling started approximately 40 years ago when representations of light interception and photosynthesis in crop canopies were developed (e.g., (Loomis and Williams, 1963)). After these early, simple models, crop simulation models have increased dramatically in complexity. Accompanying this development has been a rise in the number of model parameters. Determination of the values of these parameters often requires experimentation. However, some parameters can not be measured and are calibration within the model. Recently, some crop modellers have reached the conclusion that since crop simulation models will never be able to fully represent the complexity of the living organism, simpler crop models should be developed and viewed essentially as heuristic tools (Sinclair and Seligman, 1996). Initially, crop simulation models were developed as a method of aiding understanding of crop processes and their link with weather. However, the models are being increasingly used as management tools to develop strategies to aid crop production systems. In either case, simpler models are preferable as their results are easier to interpret.

Initially, crop models simulated either potential or water-limited production, however, increasing numbers of models now simulate nutrient limitation (e.g. nitrogen). The effect of pest and diseases, and other sub-optimal management practices that reduce actual production below the modelled potential, are usually represented by a yield gap parameter. Some of the most common crop models in use today are the cereal family of models, CERES (e.g., (Travasso and Delècolle, 1995)), and the grain legume family of models, CROPGRO (Boote et al., 1998). Crop models usually operate with a daily timestep but some models can operate some routines with an hourly timestep. For example, CROPGRO can be run with either a daily or hourly parameterisation of photosynthesis.

Matthews et al. (1997) used two rice crop models to investigate the possible impacts of climate change may have on production in Asia. Driving each model with several scenarios of climate change, including output from three GCMs, they found that production generally decreased due to increased temperatures. This was partially offset, however, by an increase in production associated with the higher CO_2 levels. Higher temperatures reduced yield due to an increased likelihood of spikelet sterility. Simple adaption strategies, such as developing varieties more tolerant to high temperatures or moving the planting date earlier in the year, were examined and shown to mitigate the effects of the climate change. The effect of high temperatures is difficult to model as it is limited to the time of flowering which occurs in the morning (Vara Prasad et al., 2000). Therefore, the accuracy of simulating this process depends on resolving the diurnal cycle in temperature.

The use of general circulation model (GCM) output to run crop models should be viewed with caution due to the mismatch in spatial scale between both models. Generally, crop models are developed to provide yields at the field or plot scale while GCMs currently operate with grid- boxes approximately 100km across. One approach to address this problem is to reduce the scale of the GCM output by down-scaling. Two options currently exist; either statistical methods or dynamical down-scaling using a regional climate model (RCM) with a finer horizontal resolution than the GCM. Tsvetsinskaya et al. (2003) explored the sensitivity of using a crop model with GCM and RCM output because the value of the high resolution information had not been clearly determined. They found that even after the results were aggregated up to the GCM scale, significant differences existed. In a similar study, (Carbone et al. , 2003) found that the simulated yield response of soybean was different when coarse (CSIRO GCM) and fine (RCM) scale climate change scenarios were used (Fig. 2.3). The high-resolution CSIRO scenario was created by imposing the model changes on observations in each 50-km grid.

Using a crop model to predict yields over a region, as opposed to the plot scale, necessarily

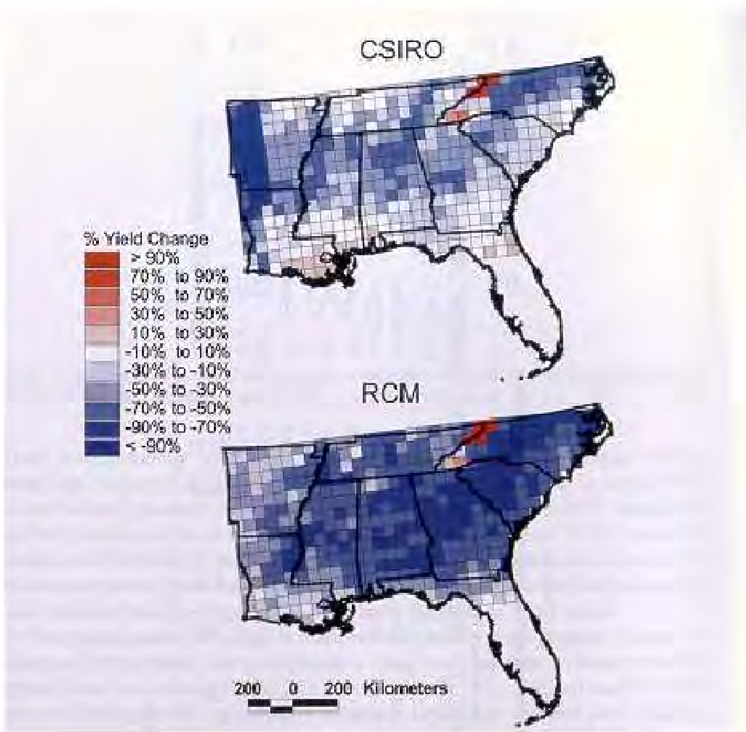

Figure 2.3: Simulated percentage soybean yield change for climate change with elevated CO_2 for CSIRO GCM and RCM simulations from Carbone et al. (2003)

requires some assumptions about the aggregation of input parameters due to the heterogeneity of the larger region. Hansen and Jones (2000) suggested that the use of effective parameters invalidating their physical interpretation. Therefore, they argued for the development of simpler crop models designed specifically to work at the larger spatial scale inherent in climate impacts studies. At such scales statistical, empirical models do have some skill but (Hansen and Jones, 2000) argue that process-based models are still needed as they mechanistically capture the effects of weather variability on crop growth.

2.3 Wheat Production in Ethiopia

In Ethiopia, wheat is grown primarily as a rainfed crop by smallholders in the highlands (Fig. 2.4). In most of the country, only a single season wheat crop is grown during the second, longer rainy season (meher) which usually starts in June. The short rains (belg), starting in March, are less reliable in most parts of Ethiopia; however, in the southeast of the country (e.g., Bale zone of Oromiyia Region), rainfall distribution is bimodal. Growing wheat in

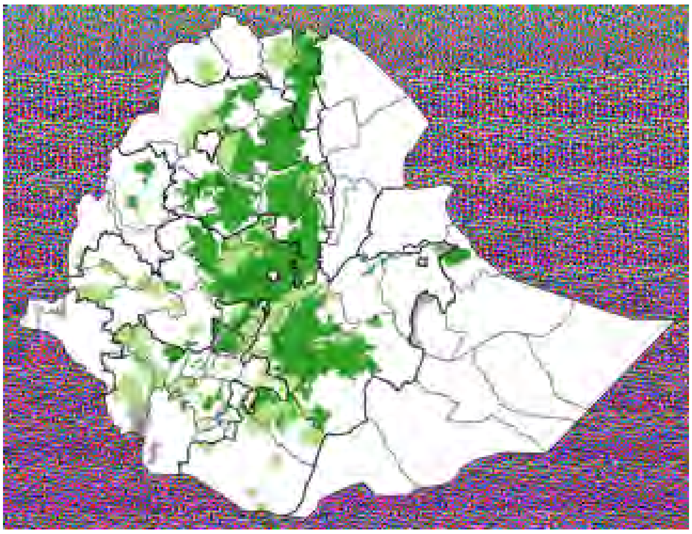

Figure 2.4: Distribution of traditional wheat production areas of Ethiopia.

belg season implies harvesting during meher, which often results in high grain moisture levels and sprouting. Thus, wheat crops are typically sown by broadcasting in June or July and harvested in November or December (Hailu, 1991). A very small area has also been grown as a winter crop under irrigation on state farms at lower elevations (Jamal, 1994).

It is largely grown in the highlands of the country and constitutes roughly 10% of the annual cereal production and plays an appreciable role in supplying the population with carbohydrates, protein and minerals (Schulthess et al., 1997). The crop is grown at an altitude ranging from 1500 to 3000 meters above sea level (masl), between 6-16^o N latitude and 35-42^o E longitude. The most suitable agro-ecological zones, however, fall between 1900 and 2700 masl (Bekele et al., 2000) . The major wheat producing areas in Ethiopia are located in Arsi, Bale, Shewa, Ilubabor, Western Hareghe, Sidamo, Tigray, Northern Gonder and Gojam zones (Bekele et al., 2000). The total wheat area and production in the Amhara region was 405,520 ha (27% of the countries coverage) and 12128.6 tons, respectively with the productivity of 1.756 t/ha (CSA, 2007) .

2.4 GLAM Model Description

GLAM has been designed to operate at the spatial scale of global and regional climate models (Challinor et al., 2004). Originally, the GLAM model was designed to simulate groundnut yield over large areas in India (Challinor et al., 2004). Based on the existing GLAM-groundnut model, a GLAM-Wheat version of the model was developed by defining the wheat growth and development parameter sets from the literature and modifying some model processes such as crop phenology and leaf area development (Li, 2008). It has been evaluated that the model can simulate wheat yield well in the larger areas in China (Li et al., 2007, Li, 2008). In this study, the GLAM-Wheat model was used to simulate the response of wheat growth, development, and yield to temperature.

The rest of this section describes the model formulation, using the following notation: capital subscripts form part of the identification of a variable type (e.g. harvest index, HI) whereas lower case subscripts distinguish within variable types (e.g. daily maximum and minimum temperatures T_{max} and T_{min}). Empirically determined coefficients are denoted by C_x in the dimensionless case, and K_x for other variables, where x identifies the particular coefficient. Subscript T is used for the two transpiration-related quantities (transpiration efficiency, ET , and transpiration rate TT) in order to distinguish them from temperature (T) and evaporation rate (E).

2.4.1 Soil hydrology

The model soil is multi-level defined by its drained upper limit, θ_{dul} (soil water at field capacity), drained lower limit, θ_{dll}, (soil water at wilting point) and saturation limit, θ_{sat} (the saturated water content) which is depth independent. Surface runoff, R, is calculated using the Soil Conservation Method (USDA-SCS, 1964) as:

$$\begin{aligned} R &= \frac{Z^2}{(Z+k_{st})} \\ K_{sat} &= K_{kS}\left(\frac{\theta_{sat}-\theta_{dul}}{\theta_{dul}}\right)^2 \end{aligned} \tag{2.1}$$

where Z is the precipitation, K_{st} is the amount of water that can soak into the soil and K_{sat} is the saturated hydraulic conductivity of the soil and K_{ks} is empirical constant.

and the change in soil moisture at each layer due to gravitational drainage is obtained using the method due to Suleiman (1999) (Equation 2.2).

$$\begin{aligned} \frac{\partial\theta}{\partial t} &= -FD(\theta_s-\theta_{dul}) \\ D = C_{d1}\theta_{dul}^2 + C_{d2}\theta_{dul} + C_{d3}, F &= 1-\frac{\ln(Q_i+1)}{\ln(K_{sat}+1)} \end{aligned} \tag{2.2}$$

where FD is the drainage rate, the factor F accounting for simultaneous inflow from the layer above, θ_s is the initial value of θ, Q_i is the incoming water flux from the layer above ($Z-R$ in the case of the uppermost layer), C_{d1}, C_{d2}, C_{d3} are empirical constants.

2.4.2 Crop development

The development of the crop is based on a thermal time (tt) approach. The thermal time elapsed within a particular growth stage, t_{tt} , between the start of the stage, t_i , and time t is given by

$$t_{TT} = \int_i^T (T_{eff}-T_b)dt \tag{2.3}$$

Thermal time is accumulated when the effective temperature, T_{eff} , is above the crop specific base temperature, T_b . The development of a growth stage is complete when t_{tt} reaches the specified duration, t_{tt_i} . For the simulation of groundnut there are four growth stages; i equals 0 from sowing to flowering, 1 from flowering to pod-filling, 2 from pod-initiation to maximum LAI and 4 from maximum LAI to maturity. The specified durations for each stage are listed in Table A.1. The effective temperature, T_{eff} , is defined as follows using the cardinal temperatures T_b , T_o and T_m , where the subscripts denote base, optimum and maximum temperatures, respectively (see Fig. 2.1).

$$T_{eff} = \begin{cases} T_b & \bar{T} \geq T_m, \bar{T} < T_m \\ T_o - (T_o - T_b)(\frac{(\bar{T}-T_o)}{(T_m-T_o)}) & T_b \leq \bar{T} \leq T_o \\ \bar{T} & T_o < \bar{T} < T_m \end{cases} \tag{2.4}$$

where $\bar{T}$ is the daily mean temperature.

The crop is sown when the soil moisture of the top levels in the soil model exceeds a fraction (C_{sow}) of the field capacity. Emergence occurs some specified time, t_{em} later. The crop is harvested either when the final growth stage has been completed, or if the crop experiences terminal water stress during the last two growth stages, defined as when available soil water is less than 70% of field capacity.

2.4.3 Crop evaporation and transpiration

Transpiration (TT) and evaporation rates (E) are determined by considering separately the limitations imposed by plant/soil structure, energy availability, and water availability. Potential values of E and TT are defined as being limited by only the first two of these constraints. The physiologically limited transpiration is modelled using an empirical relationship based on the data of Azam-Ali (1984).

Transpiration plays a key role in the growth of the crop, determining both the accumulation of biomass and, by moderating water uptake from the soil, the rate of leaf canopy expansion. The actual rate of crop transpiration is the minimum of energy, physiology and water limited rates of transpiration, which are calculated separately. The physiological-limited rate of transpiration is constant above a critical LAI (L), and is a linear function of LAI below it:

$$T^{p}_{Tpot} = \begin{cases} T_{Tmax}\left(1 - (\frac{L_{cr}-L}{L_{cr}})\right) & L < L_{cr} \\ T_{Tmax} & L \geq L_{cr} \end{cases} \tag{2.5}$$

where L_{cr} is a critical threshold value of L and T_{Tmax} is the maximum possible physiological potential transpiration rate.

Energy-limited transpiration(E_e) is derived from energy-limited evapotranspiration (E^e) as defined by the Priestley-Taylor equation (Priestley and Taylor, 1972):

$$E^{T}_{pot} = E^e + T^e_T = \frac{\alpha}{\lambda}\frac{\Delta(R_N - G)}{\Delta + \gamma} \tag{2.6}$$

where R_N is the net all-wave radiation, G is the soil heat flux, λ is the latent heat of vapourisation of water, $\Delta = \partial e_{sat}/\partial T$, determined after Bolton (1980), and γ is the ratio of the specific heat of air at constant pressure (c_p) to the latent heat of vapourisation of water (L). The inclusion of the Priestley-Taylor coefficient (α) accounts for the effect of atmospheric vapour pressure deficit.

The net radiation is estimated from the solar radiation using

$$R_N = (1 - A)S_{rad} \tag{2.7}$$

where S_{rad} is the incoming short-wave radiation and A is the mean albedo of the surface. This assumes that net long-wave radiation is zero, which is very reasonable under monsoon (i.e. cloudy) conditions. During monsoon breaks, and during the dry season, clear skies mean that R_N can be over-estimated by up to 100 W m^{-2}. However, sensitivity studies have shown that this has an insignificant effect on the model simulations.

E^{T}_{pot} is then partitioned into soil evaporation, E^e , and crop transpiration, T^e_T , according to the light interception by the canopy which is modelled using the Beer-Bougert equation:

$$E^e = (1 - C_G)E^T_{max}e^{-kL}$$

$$\text{and} \tag{2.8}$$

$$T^e_T = (1 - e^{-kL})E^T_{max}$$

where C_G is the constant in the equation for the soil heat flux, $G = C_G R_N e^{kL}$, k is the extinction coefficient. E^T_{max}, The maximum possible energy-limited evapotranspiration is given by setting $G = 0$ in Equ. (2.8).

The potential (energy and soil-structure limited) daily evaporation is modelled by

$$E^s_{pot} = \frac{E^e}{t_R} \tag{2.9}$$

where t_R is the number of days since the daily total rainfall was greater than a threshold value of P_{cr}. This threshold value was chosen to be just above zero (1 mm) to avoid unrealistically high potential evaporation just after low rainfall.

The potential energy- and physiology-limited rate of transpiration is then

$$T_{T_{pot}} = min(T^p_{T_{pot}}, T^e_T) \tag{2.10}$$

The limitation due to water availability is calculated based on the potentially extractable soil water, θ_{pe} , which is a function of soil water content, root length density and time. If θ_{pe} is less than E^T_{pot} then water-limited transpiration and evaporation from the soil, θ_{pe} is scaled by their relative contributions to E^T_{pot} .

$$T_T = \begin{cases} T_{T_{pot}} & and \quad E = E_{pot} \quad for \quad \theta_{pe} \geq E^T_{pot} \\ \theta_{pe}\left(\frac{T^e_T}{T^e_T + E^e}\right) & and \quad \theta_{pe}\left(\frac{E^e}{T^e_T + E^e}\right) \quad for \quad \theta_{pe} < E^T_{pot} \end{cases} \tag{2.11}$$

2.4.4 Crop growth

The crop is characterised by its biomass, LAI, and root profile. The growth of the crop leaf area is determined as follows:

$$\frac{\partial L}{\partial t} = \begin{cases} \left(\frac{\partial L}{\partial t}\right)_{max} C_{YG} min\left(\frac{S}{S_{cr}}, 1\right), & i(cropstage > 3) \\ 0, & i(cropstage = 3) \end{cases} \tag{2.12}$$

where $(\partial L/\partial t)_{max}$ is the prescribed maximum rate of leaf growth and

$$S = \frac{T_T}{T_{T_{pot}}} \tag{2.13}$$

is the soil water stress factor, which begins to affect growth at values less than the critical threshold value S_{cr}. T_T and $T_{T_{pot}}$ are the transpiration rate and potential transpiration rate, respectively. C_{YG} is the yield gap parameter, used to reduce LAI from the physical value to an effective value which accounts for the mean effects of pests, diseases and non-optimal management. Yield potential (maximum obtainable yields as determined by weather and crop) may be simulated by setting $C_{YG} = 1$.

The rate of biomass accumulation is obtained from transpiration via the transpiration efficiency, which below a maximum value of crop-dependent maximum transpiration efficiency ($E_{TN,,max}$) is determined by the crop-dependent normalised transpiration efficiency (E_T) and the vapor pressure deficit, V:

$$\frac{\partial W}{\partial t} = T_T min\left(\frac{E_T}{V}, E_{TN,max}\right) \tag{2.14}$$

where V is the vapour pressure deficit ($VPD = e_{sat}(\bar{T}) - e$, where e is vapour pressure), E_T is the normalised transpiration efficiency in Pa (i.e. V transpiration efficiency in gkg^{-1}), and $E_{TN,max}$ is the maximum transpiration efficiency in gkg^{-1} .

The useful crop yield is determined as a fraction of the biomass via the harvest index H_I:

$$Y = H_I W, \qquad \frac{\partial H_I}{\partial t} = \text{prescribed-constant} \tag{2.15}$$

The maximum rate leaf growth is given by the crop-dependent maximum rate of LAI increase $(\partial L/\partial t)_{max}$, before Stage 3. LAI growth rate is attenuated by a yield gap parameter $C_{YG}(\leq 1)$, which represent crop development due to non-optimal crop management practices. Water deficits will also begin to affect the leaf development when the water stress S is below a crop-dependent threshold S_{cr}.

The root system in GLAM are represented by the volumetric root length density at surface ($z = 0$) and at the root extraction front ($z = z_{ef}$). The variation with depth, and in relation to the LAI, is governed by the following equations:

$$\begin{aligned} \frac{\partial l_v(z=0)}{\partial L} &= \text{prescribed constant} \\ V_{EF} &= \text{prescribed constant} \\ l_v(z=z_{ef}) &= \text{prescribed constant} \end{aligned} \tag{2.16}$$

where l_v is the root length density by volume, z denotes depth into the soil, z_{ef} is the depth of the root extraction front and V_{EF} is the extraction front velocity.

The vertical profile for the volumetric root length density is given by a linear interpolation of l_v between the surface and the extraction front. In the model, the rate of root density increase depends on the rate of leaf growth; non-optimal environmental condition thus affects the root development indirectly through environmental stresses on leaf development.

One feature of GLAM to note is the soil-crop feedback within the model. This is best

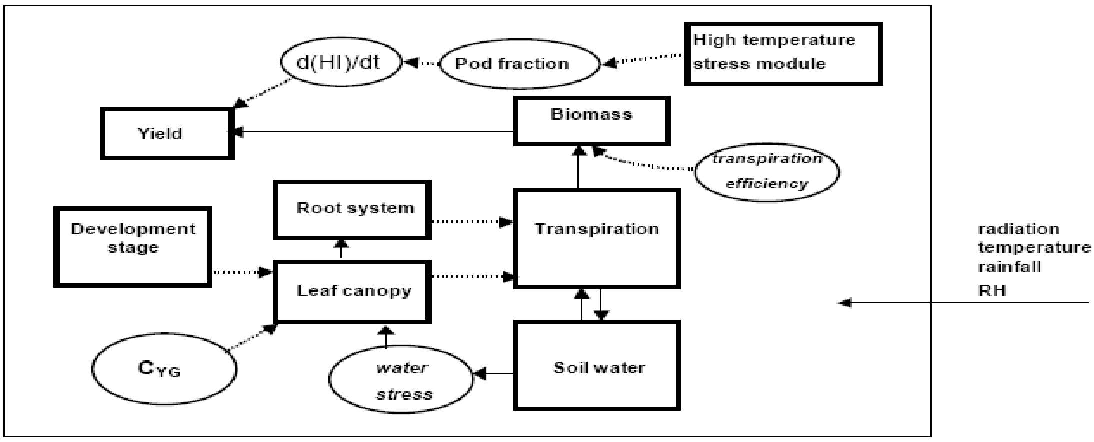

Figure 2.5: Relational diagram of GLAM. Rectangles represent state variables, ovals represent auxiliary variables. Solid lines represent flows of material while dashed lines represent flows of information. Daily mean weather inputs are on the right. HI is harvest index.

illustrated with the schematic of the relations of the major model components of GLAM shown in Fig. 2.5. In the model, soil water availability affects crop development through its ability to satisfy the transpiration demands as well as its effect on leaf canopy and root development. The soil-leaf-root feedback loop is important in determining the impact of rainfall variability in the final crop yield at harvest. Soil water stress at the early stages of crop development (before LAI attained its maximum value) results in lower LAI and volumetric root density as the crop matures. This limits transpiration due to lower soil water extraction by the roots (2.1) and smaller leaf canopy. Even when soil moisture is sufficient later in the crop season, the crop is unable to utlise the available soil moisture. On the other hand, when soil moisture is sufficient in the earlier crop stages, near optimum leaf canopy and root growth can be attained and consequently, is able to better utlise soil moisture in the later crop stages compared to the preceding case. Hence, for GLAM, the impact of soil moisture deficits on crop development can be unequal depending on their occurrence with respect to the crop stages. Although other input weather parameters affect the biomass accumulation, their effects on crop development in general is comparatively lower than that of rainfall in practice. This is primarily due to the absence of coupling between these inputs, except temperature, and the leaf and root development, as well as the lower variability of these parameters compared to that of rainfall. Although the duration of each crop stage depends on temperature, the relatively low variability of daily average temperature usually has a lower impact than rainfall for GLAM in practice. The inclusion of effect of crop development has been recently addressed in GLAM (Challinor et al., 2005c) in response to the importance of temperature stress on various crops (Ferris et al., 1998; Ismail and Hall, 1999; Prasad et al., 2000; Matsui et al., 2001) especially during flowering (Wheeler et al., 2000). However, this is not included in the current discussion.

Chapter 3

Regional Climate Model Validation Over Ethiopia

3.1 General

Understanding and predicting how the climate of Africa will change over the next century is an issue of increasingly urgent importance. African society and its economy are strongly dependent on its agriculture (Challinor et al., 2007). One measure of this economic dependence is that agriculture is estimated to account for 30% of African GDP (IPCC, 2007b), while in rural Africa, over 70% of the population derive the bulk of their income from agriculture (Jayne et al., 2003). A substantial proportion of this agriculture is not irrigated, and instead depends upon there being sufficient rainfall throughout the growing season to sustain crop growth, for example, nearly 90% of cereals in sub-Saharan Africa are rainfed (Cooper, 2004).

It is clear, therefore, that relatively small changes in rainfall will have large socioeconomic impacts. Changes in the seasonal cycle of rains, in the geographical distribution or even the year-to-year variability of rainfall can drastically change rainfed crop yields (Challinor et al., 2004, 2005a). Similarly disease transmission is sensitive to the seasonal cycle and geographical distribution of rainfall, such as the case for malaria in the epidemic regions of Africa (Morse et al., 2005). It has been suggested that by the end of the century the highlands of Ethiopia, Kenya, Rwanda and Burundi, which are currently malaria free, may become highly suitable for malaria mosquitoes (IPCC, 2007b). Understanding the human-scale impacts of climate change in Africa requires detailed predictions of how rainfall may change in the future, particularly over the next few decades.

Our understanding of how climate will change over the next century is largely based on the projections of the global coupled climate models used in the Fourth IPCC assessment report on climate change (IPCC, 2007a). In order to have confidence in the projections of climate models it is essential that they can simulate the present day climate. On global scales, climate models have already shown they can make credible simulations of the temperature record of the 20th century (IPCC, 2007a) and of the response of global temperatures to major climatic events, such as the Mount Pinatubo eruption and the El Niño phenomenon in the Tropical Pacific. However, one of the key challenges for climate models and climate science is that they should be capable of not only making predictions at the global scale, but that their predictions should also be relevant at the human-scale. Central to this is understanding and predicting how climate will change at regional scales, and for variables such as rainfall.

The current generation of global climate models generally operate at much larger spatial scales than those that are important for determining climate impacts. For example, crop models tend to operate at spatial scales of regions, or even at the spatial scales of individual fields (Hansen and Jones, 2000). Down-scaling predictions of rainfall using regional climate and statistical models are possible solutions for providing information at smaller spatial scales, but their use can be problematic (Jenkins and Lowe, 2003). The need for detailed predictions of rainfall, that are vital to the future of the African continent, cannot be met at the present time. Global climate models, however, are developing at a rapid pace. In particular a range of global climate models have been developed that in principle should be more capable of simulating climate at regional scales (Shaffrey et al., 2008). These global climate models have higher resolutions than those used in the current generation of climate models.

In order to understand the impact of resolution it is necessary to understand how climate models are built. The skeleton of a climate model is its grid. Within each part of the grid (the grid-box) a climate model represents temperatures, winds, clouds and rainfall (along with many other variables needed to simulate the complexity of the climate system). A high resolution climate model with small grid-boxes can represent smaller scale processes than a coarser resolution climate model. Higher resolution climate models should be more capable of resolving local circulations, and capturing important processes such as the impact of mountain ranges and variations of the underlying surface on the geographical distribution of rainfall.

Increasingly the outputs from climate models are being used to drive climate impact models to understand the sensitivity of the human-scale impacts to climate change. Increases in the resolution of climate models are an important for reducing the disparity in spatial and temporal scales that presently exists between climate models and climate impact models. The hope is that as climate models become more capable of resolving regional scales they will be more capable of directly driving climate impact models.

Evaluating climate models over regional scales is therefore central to assessing the credibility of present day climate simulations. Unfortunately, over much of Africa the lack of long-term observations and the sparse nature of the observing network means that African climate and its variability are often poorly known, making comparisons with climate models problematic. Furthermore, the lack of observations makes it extremely difficult to understand what processes are being represented poorly, which makes improving climate models a formidable task. However in some regions enough observations exists to make a meaningful comparison between climate models and observations. Over Ethiopia, a climatology of rain gauge measurements has recently been produced (Diro et al., 2008), which for the first time allows a regional evaluation of rainfall simulations from climate models to be made over Ethiopia.

Ethiopia presents a particularly difficult test for climate models. The central part of Ethiopia is dominated by the East African Highlands, which split the country climatically. To the south and east the land is semi-arid and the rains fall in two short spells either side of the dry season of Kirmet (June to August). To the north and west, the vegetation is more lush, and Kirmet is the major rainy season (Diro et al., 2008). This split in the geographical distribution of rainfall, and the different seasonal cycles in different regions of Ethiopia, make the task of simulating Ethiopian rainfall extremely challenging. Furthermore, climate models need to be able to capture the processes that influence the year-to-year (interannual) variability of Ethiopian rainfall. Variations of El Niño, the Indian Monsoon and the position of the African Easterly Jet all impact on the rainfall over Ethiopia. Disentangling these remote influences on the climate of Ethiopia, and correctly simulating them in a climate model is an exceptionally difficult task.

In this chapter we present a validation analysis of a recent climate simulation over the Ethiopian region with the Abdus Salam International Centre for Theoretical Physics (ICTP) climate model, RegCM-4.0. The simulation analyzed here covers the 14 year period of 1995-2008 over a domain encompassing Ethiopia (our main region of interest). The boundary conditions for the model simulation are obtained from a reanalysis of observations, and different statistics of simulated temperature and precipitation, covering a range of spatial and temporal scales, are validated against gridded datasets.

3.2 Model description

The RegCM-4.0 version used here was originally developed by Giorgi et. al. (1993a,b) and later modified and improved as described by Giorgi and Mearns (1999) and Pal et al. (2007). It is a hydrostatic and terrain following sigma vertical coordinate model whose dynamical core is essentially the same as that of the hydrostatic version of the National Center for Atmospheric Research (NCAR) and the Pennsylvania State University mesoscale model MM5 (Grell et al., 1994). The Biosphere−Atmosphere Transfer Scheme BATS (Dickinson et al.,

1993) is used to represent surface processes while boundary layer physics is described via the non−local vertical diffusion scheme of Holtslag et al. (1990). Other physics parameterization schemes include the radiative transfer package of the NCAR Community Climate Model, the version CCM3 (Kiehl et al., 1996), the mass flux cumulus cloud scheme of Grell et al. (1993) to represent convective precipitation and the resolvable scale precipitation scheme of Pal et al. (2000), which includes a prognostic equation for cloud water and allows the determination of sub-grid scale cloud fraction.

3.3 Model Configuration

The selection of the model domain, its size and the resolution are important issue for regional climate modeling (Salzmann, 2006, Anyah, 2005). The model domain should be sufficiently small that the synoptic circulation does not depart from that of the driving GCM. On the other hand, the model domain should be large enough to avoid an increased role of the lateral boundary effect, which prevent the development of small-scale details of the local climate Krichak (2008). This means that the optimum domain size should be one where large-scale circulation in RCM is constrained to follow the driving GCM fields, but the finer mesoscale systems also have enough space to fully develop. The domain should also includes all areas where forcing and processes are dominant elements for the climate of the specific region.

In this thesis, the model is configured with horizontal resolution of 50 km with its standard configuration of 18 vertical σ-levels and model top at 50 hpa. The domain size and location is selected so that the main large scale forcing like ICTZ, the nearby subtropical high pressure systems and the main monsoon systems are included. It is centered at 9.5^{o}N, 35^{o}E and covers 96 grid points in the y-direction and 224 grid points in the x-direction (Fig 3.1).

Observed sea surface temperature (SST) derived from the Optimum Interpolation sea surface temperature (OISST) one-degree gridded data from National ocean and Atmosphere Administration (NOAA) at weakly scale is used in the Simulation. Constant (in time) surface parameters (topography, land use, vegetation, soil type etc) are determined from a 10-

min archive. Meteorological initial and time-evolving boundary conditions (for the wind components, temperature, surface pressure, and water vapor) are taken from global reanalysis (ERA-Interim) data developed by European Center for Medium range weather Forecast (ECMWF) and the lateral boundary conditions are relaxed exponentially.

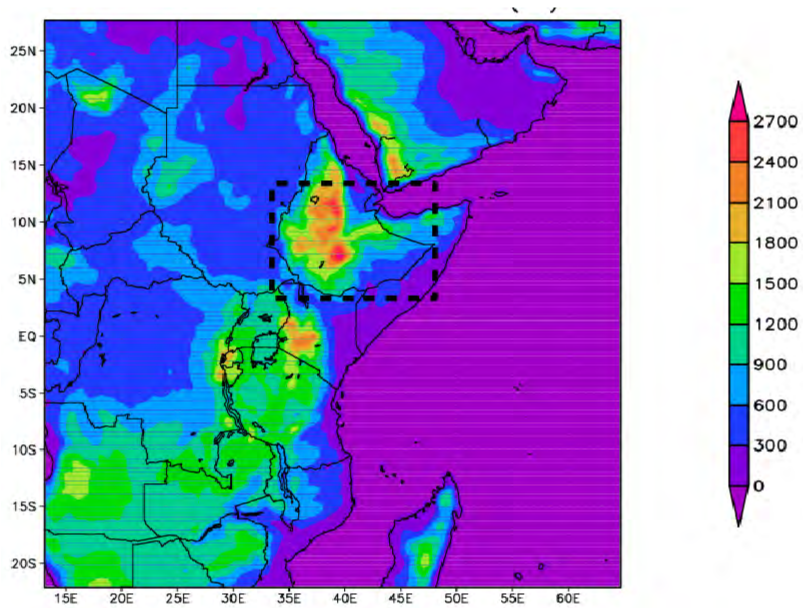

Figure 3.1: Model domain at a grid spacing of 50 km. The box shows the interior domain (not directly affected by the lateral buffer zone and marked with black broken lines): 3^o-15^o N and 35^o-49^o E respectively.

3.4 Validation of RegCM-4

Given the relatively small size of the domain, we do not expect that the model will substantially modify the basic features of the synoptic systems entering the domain. Rather, our analysis focuses only how the model simulates surface climate (precipitation, which is critical variable for crop models) for Kirmet season(the major growing season in Ethiopia), in response to the large scale forcing imposed by the ERA-Intriem reanalysis and by local topographical features.

3.4.1 Spatial Pattern

In this section the ability of RegCM climate model to simulate the geographical distribution of rainfall during the season of Kirmet (June to August), when most of the rain in Ethiopia falls in the regions to the north and west of the East African Highlands.

The geographical distributions of kiremit season rainfall from RegCM and GPCP datasets are shown in Fig. 3.2. The distributions of rainfall are plotted at the resolution of climate model grids. The distribution of rainfall is correspondingly better represented, with the maxima of rainfall situated on the upwind slope of the highlands. The maxima of rainfall seen in RegCM in the north-west of Ethiopia is situated closer to the maxima seen in the GPCP dataset. During Kirmet there is a strong south-east to north-west gradient of rainfall across the Ethiopia. To the north-west there is in excess of 10 mm/day of rainfall during Kirmet simulated by RegCM . In stark contrast, there is less than 1.8 mm/day of rainfall in the south-east. Generally, RegCM is capable of capturing the general pattern of rainfall in the Ethiopia during Kirmet. When we compare the simulation to GPCP datasets, there is a little overestimation over the highland part of Ethiopia.

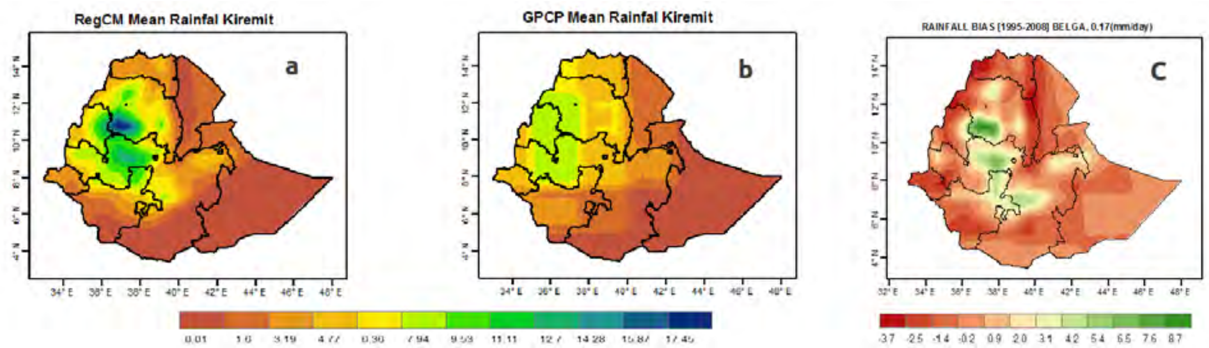

Figure 3.2: Comparison of spatial distribution rainfall for kiremit season during the period 1995-2008 (mm/day) (a) model simulated rainfall (b) GPCP rainfall (c) Differences between model and GPCP rainfall.

Seasonal precipitation bias fields for the 1995-2008 period are shown in Fig. 3.2c . For the interior domain average, an overestimation of precipitation is found in every season when compared to GPCP, about 0.17 mm/day in Kirmet and a negative bias is found in the low-land area and central, south-east and south-west portions of the interior domain. Rainfall is generally underestimated in the southern portions of the domain. The largest positive biases are found over the highland regions in this colder seasons. Generally, the comparison of the model data with the GPCP precipitation shows that the RegCM has lower precipitation almost everywhere in the interior-domain except over Ethiopian highlands. This means that RegCM is underestimating the precipitation almost everywhere in the interior-domain compared to the observed datasets. Focusing on the innermost portion of the domain covering the Amhara region (our main area of interest), the bias compared to GPCP is around 2mm/day or less in all seasons.

3.4.2 Monthly rainfall

The mean annual cycles of Ethiopian monthly rainfall obtained from the RegCM simulation and observation(GPCP) are shown in Fig. 3.3. The model generated annual cycles of rainfall match reasonably well with the observed data. The model produces excess rainfall during the months of January and September - December.

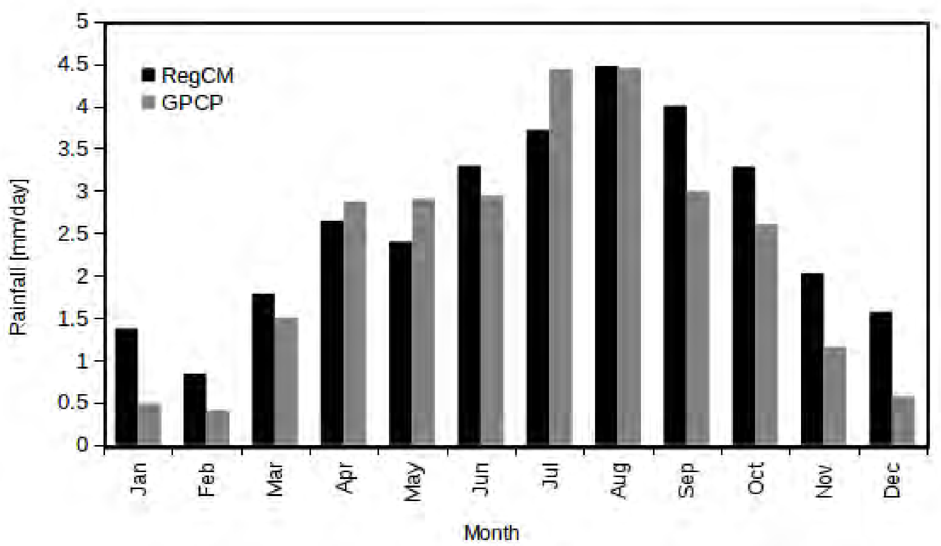

Figure 3.3: Comparison of simulated monthly rainfall (mm/day) with the observed data in Ethiopia during the period 1985 -2008.

The model overestimates rainfall for the transitional month(from wet to dry season) of September to the starting month of Belg, i.e., the month of February. During March to August, the model estimates almost the same as the observed rainfall. In fact, the characteristics of precipitation systems, especially the vertical height and precipitation strength in this region are different in different rainy periods, whereas the use of same cloud parameterization cannot represent variable atmospheric conditions in different periods (Islam and Uyeda ,2008).

3.4.3 Seasonal rainfall

It is seen that the model has overestimated rainfall in Bega (Oct-Jan) seasons. During the Belg (Feb-May) and Kirmet (Jun-Sep) seasons, model simulated values are almost the same as the observed values Fig. (3.4).

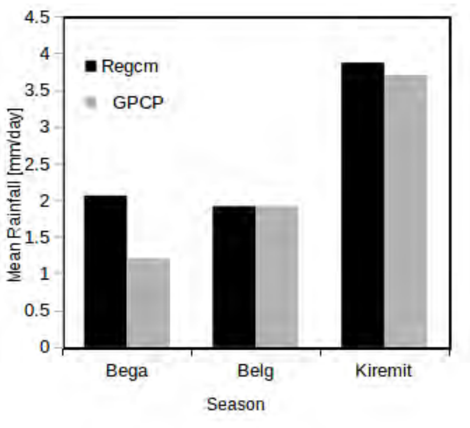

Figure 3.4: Comparison of simulated Seasonal rainfall (mm/day) with the observed data in Ethiopia during the period 1995 -2008.

The average Kirmet rainfall (JJAS) for the period of (1995 - 2008) simulated by RegCM4 is 3.87 mm/day with a correlation of 0.79. The model seems to have overestimated the All Ethiopian Kirmet rainfall; its variability is almost the same as the observed values. During the Bega, Belg season model simulated rainfall is 2.06 and 1.92 mm/day with a correlation of 0.62 and 0.64.

3.5 Kirmet Rainfall Variability

Rainfall is essential for non-irrigated agriculture practice over most of the country. The wester highlands have particularly high rainfall averaging more than 450 mm seasonally in many areas. Rainfall is lower with the loss of elevation towards the east. Most of eastern lowlands are dry for any crop production.

Fig. 3.5 shows the variability kiremit seasonal rainfall over Ethiopia. The coefficient of variation calculated as the standard deviation divided by the mean is often represent how rainfall is variable/ stable across the country. The coefficient of variation of kiremit rainfall is calculated for the past 14 years. High variability (greater than 30% variability) in simulated rainfall represents increased risk for farmer who depend on rainfall for crop production. Medium variability, represented by the lighter blue areas is common over the highlands of Ethiopia. Although Afar region experiences little rainfall variability, it also experience low seasonal rainfall rainfall variability making this area unstable for crop production.

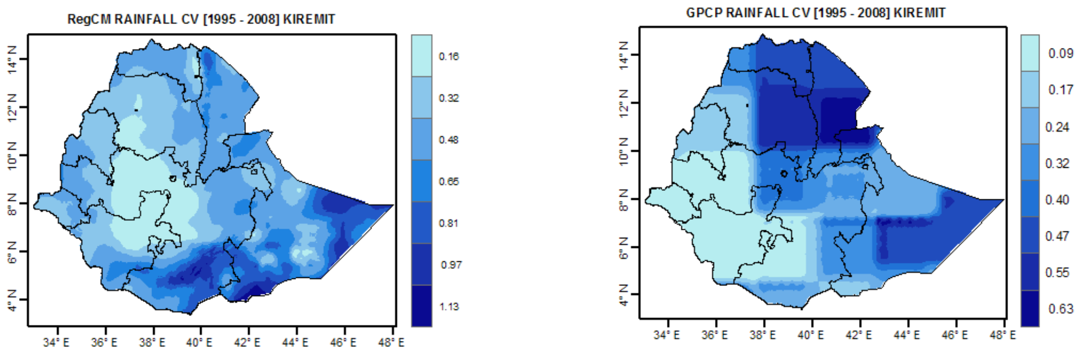

Figure 3.5: Comparison of simulated Seasonal rainfall (mm/day) with the observed data in Ethiopia during the period 1995 -2008.

Chapter 4

Application of Regional Climate Model in crop yield estimation

4.1 General

Utilisation of satellite remote sensing in agriculture in Africa has been a subject of intensive research. This is primarily due to the large spatial coverage and good temporal resolution of satellite information, which complements ground-based agrometeorological observations for the monitoring of crop growth. This data is vital for many regions of Africa because of the sparse and often poorly maintained hydrometeorological networks (Washington et al., 2006). National, regional and international agencies concerned with food securities in the continent have adopted satellite-based information with various levels of sophistication, for the in-season monitoring of crop growth as well as crop production forecasting for the planning of food relief operations, when necessary (Rijiks et al., 2003, Verdin et al., 2005).

An alternative method of using satellite-based rainfall estimates for crop production prediction is to assimilate this information into process-based crop models that are able to simulate crop processes. These are more complex models, which in theory, are capable of capturing more subtleties in the intraseasonal variability of weather that may elude the more empirical CSWB models. Descriptions of many different process-based crop models are available in the literature. A good review can be found in Matthews et al. (2000), Thornton et al. (1997)

demonstrated the potential of using satellite RFE and other ground-based data in a mechanistic crop model (CERES-millet) for millet yield prediction in Burkina Faso. Although the potential of such crop models has been demonstrated, the study also highlighted the overhead of assembling the necessary large amount of input information.

An additional issue in using these mechanistic crop models in operational crop yield forecasting is that most of these models are designed for small homogeneous spatial units (field or plot). Therefore, they are sensitive to spatial heterogeneity in agrometeorological conditions, soil types and management practices. Consequently, exhaustive spatial information is required to implement these crop models for yield prediction over a large spatial extent. To apply such mechanistic crop models directly on a spatial scale larger than its original working scale by spatially upscaling model inputs, can result in bias in model prediction. This happens as a result of the non-linearity of model processes and the emergence of new processes due to the spatial interaction not accounted for within the models (Hansen and Jones, 2000, Faivre et al., 2004). For Africa, regions in which such crop forecasting systems are vital often lack the spatially high-resolution data required for such crop models to be practical in operation. Hence, opportunities for applying these crop models for regional crop production prediction are at present limited.

The limitations of using process-based crop models in data-sparse region could potentially be overcome. Recent advances in assimilating satellite-derived Vegetation Index fully into mechanistic crop models (Moulin et al., 1998) offers the potential of offsetting errors in simulated crop development due to uncertainties in input and model calibrations, by nudging some of the model crop state variables (example, biomass or Leaf Area Index) towards those derived from satellite imageries, in the course of the model simulation (Pellenq and Boulet, 2003). However, most of these investigations are largely confined to developed countries in Europe and the US. Another plausible solution for the problem of utilizing process-based crop models in the absence of exhaustive crop model inputs is by model reduction; Roebeling et al. (1999) uses satellite derived solar radiation and evapotranspiration in the EARS-CGS crop model which does not rely on a soil hydrological sub-model to simulate crop transpiration. They reported satisfactory yield predictions for maize at provincial level in Zambia and Zimbabwe. Another crop model with potential for application for data scarce regions in Africa is the General Large Area Model for annual crops (GLAM) (Challinor et al., 2004), a process-based crop model that is designed for large area application, combining the advantages of empirical models and mechanistic models to achieve low input requirement, while maintaining the ability to simulate crop processes. GLAM has shown good performance in hindcasting of district-level rainfed groundnut yields for India (Challinor et al., 2004, 2005a,b). However, its performance in Africa especially in Ethiopia using RegCM-based rainfall estimates as inputs has not been tested.

The main purpose of this chapter is to investigate the feasibility of using GLAM for crop yield prediction for regions where crop production is water-limited, focusing primarily on the model's ability to predict crop yields with RegCM model output data as input. The observed yield from CSA are used for skill comparison in yield prediction. The observed yield data is also useful as a reference when exploring the various aspects of rainfall-yield interactions in GLAM. The most important wheat production region of the Ethiopia, Amhara regional state were used as case studies.

As crop model yield sensitivity to inter-seasonal and intra-seasonal rainfall has been reported in various studies (Mearns et al., 1996, Riha et al., 1996, Hansen and Jones, 2000, Challinor et al., 2005a). Another area to be explored concerns the crop model yield responses to errors in satellite RFE. Of particular relevance to the present discussion is the investigation by Challinor et al. (2005a), who reported improvement in GLAM yield prediction by correcting systematic bias in rainfall for the case of Indian groundnut. In the present case study several cases of GLAM crop processes with different rainfall inputs were analysed in detail to understand how crop model yield error can arise from differences in rainfall inputs. This analyses served to compliment those observations in Challinor et al. (2005a). To this end, a set of preliminary experiments has been conducted to gain a basic understanding on GLAM model yield responses to simple rainfall distributions. The observations from these preliminary experiments are used as a basis for analysing a few cases of RegCM-4 based rainfall and GPCP-rainfall driven crop models. The effect of systematic bias in RegCM-rainfall on model yield are discussed through a detailed analysis of one year when bias in RegCM leads to overestimation of Amahara yield for GLAM.

Section 2.4 gives a brief description of GLAM. The remainder of this chapter is arranged as follows: Section 4.2 describes the method that used to analysis, the dataset used in this study and the calibration of the crop models for wheat cultivation in the Amhara Region.

4.2 Modeling and analysis methods

4.2.1 The crop model

The crop model used in this study was the General Large-Area Model for annual crops. It is fully described in (Challinor et al., 2004). It is a model of intermediate complexity, with parameterizations that seek to avoid a large crop model input data requirement, while capturing the interactions between climate and crop. It is designed to run on any spatial scale at which a relationship exists between crop and climate (Challinor et al., 2003), and it has been run successfully over India at a 2.5^o resolution using observed gridded data and GCM ensemble output.

GLAM is a process-based crop model with a daily time step, allowing it to resolve the impacts of subseasonal variability in weather. It has a soil water balance with 25 layers, which simulates evaporation, transpiration, and drainage. Transpirative demand is simulated according to Priestley and Taylor (1972), and the supply of water according to root water uptake. Roots grow with a constant extraction-front velocity and a profile that is linearly related to leaf area index (LAI). LAI evolves using a constant maximum rate of change of LAI that is modified by a soil water stress factor (the ratio of water supply to transpirative demand). Separate simulation of biomass accumulation, by the use of transpiration efficiency [an input parameter, normal ized by the vapor pressure deficit (VPD) and based on observations], allows specific leaf area (SLA; the mass of leaf per unit area of leaf) to be used as an internal consistency check: leaf area and leaf mass can be derived independently of each other and can be used to calculate values of SLA that can be compared to the typical observed values. The objective of the model is to reproduce the impact of weather on observed crop yield. This aim leads to two particular model characteristics: first, complexity at a level that is far removed from the yield-determining processes is omitted (see Sinclair and Seligman 2000). In general, simple parameterizations are favored over more complex methods. Second, of the impacts on yield due to factors other than weather (biotic stresses such as pests, diseases, weeds, and abiotic management factors), only two are modeled explicitly- (i) planting date, which occurs on the first day within the prescribed planting window for which the available soil moisture is over 50% of the maximum, or at the end of the window if no such day is found; and (ii) soil hydrological properties, which are derived from the prescribed saturated upper limit and drained lower limit of the soil. GLAM uses a single parameter to account for the yield gap (the reduction in yield from climatically determined attainable values to actual values due to the impact of biotic stresses and suboptimal management). While this is a simplification, it allows the model to focus on the crop-climate interaction.

4.2.2 Weather, Yield and Soil Data

Weather inputs for the crop model(GLAM) are daily mean values of minimum and maximum temperature, and daily total rainfall and solar irradiance. These inputs are extracted from the regional climate model output. So, RegCM wheather data is used as input to GLAM over the study study area (Fig. 4.2). The data cover the period from September 1995 to August 2008. Daily values of all the inputs are calculated as the average of the RegCM4 six-hourly temperature. The RegCM4 dataset is compared with the dataset of the GPCP. Rather than regrid either dataset and degrade the information, RegCM4 grid cells were assigned uniquely to GPCP grid cell according to the region of the greatest overlap. Both data sources have associated errors, but the GPCP dataset is based solely on observations, and is expected to provide a better estimate of rainfall over the area covered.

The yield data for calibration (1995-2001) and evaluation (2002 - 2008) of the model came from the database of the Annual Agricultural Sample Survey‘s of the CSA for the period 1995-2008. Yields tend to increase over time, as improved varieties and management methods are employed. This trend will not be predicted by the model, and some assumptions must be made in order to remove this trend. In this study we have taken the common step of assuming a linear technology trend. The results of this study may depend to some degree on how the technology trend is modeled; it is, therefore, worth considering other options. Because explicit modeling of the underlying technological processes would require a knowledge of crop variety and management, two practical options for modeling the yield technology trend remain-(i) fitting a given trend parameterization (e.g., polynomial) using least squares, and (ii) assuming the form of the probability density function (PDF) of detrended yield, and of the form of the technology trend, with subsequent determination of the trend using maximum likelihood (Moss and Shonkwiler 1993;Ramirez et al. 2003). Because the form of the PDF of yield cannot be determined a priori (e.g., Atwood et al. 2003), we use the first of these methods to determine alternative technology trends; linear ($y = a+bt$), quadratic ($y = a + bt + ct^3$), and cubic ($y = a + bt + ct^3 + dt^3$) trends were fitted to either the whole time series or piecewise to each half of the time series. The weather and yield datasets overlap for the period of 1995-2008 for 64 grid cells across Amhara region. Hence, this is the spatiotemporal domain used for this study (Fig. 4.2).

Soil hydrological properties were derived from FAO/UNESCO (1995). The textural categories were used to assign each $0.5^o \times 0.5^o$ grid square to one of seven classes, five ranging in texture from sand to clay, with the addition of lithosol and organic categories (Tate, 2001). Values of the soil parameters (θ_{sat} , θ_{ll} and θ_{dul}) for each run were obtained by averaging onto the model grid. To account for the uncertainty in the representation of soil hydrological parameters over such large areas using these parameters, three possible sets of the soil parameters were defined, corresponding to mean, upper, and lower values of the maximum available soil water within each of the seven classes. These three sub-classes are referred to

Figure 4.1: Zonal linearly detrended wheat yields (kg/ha) in Amhara Region, for the period 1995-2008, on the RegCM grid.

as course, medium and fine. Soil in the Amhara crop cultivation region is generally loamy sand and sandy loam for the top 50 cm of the soil with an increasing amount of clay with depth (FAO/UNESCO, 1995). Drained lower limits and drained upper limits were adopted as 0.04 0.14 and 0.14 0.24 from the range of values for soil water content at wilting point and field capacity recommended by Zobler (1986) for the two soil series. These are reasonable ranges considering the total available water in the soil is 150-200 mm for Southern Amhara, while Northern Amhara is about 100-150 mm (FAO/UNESCO, 1995).

4.2.3 Crop model calibration and parameters selection

The model has been calibrated and tested for wheat in Amhara region, Ethiopia, using thirty-five $0.5^o \times 0.5^o$ grid cells. The summer (June or July sowing, September-December harvest) seasons were simulated. The current study focuses mainly on 11 administrative zones grid cells (Fig. 4.2), These were chosen for their geographical and meteorological diversity, and also the region accounted for 27% of Ethiopia's total wheat production over the study period (1995-2008) (See Section 2.3).

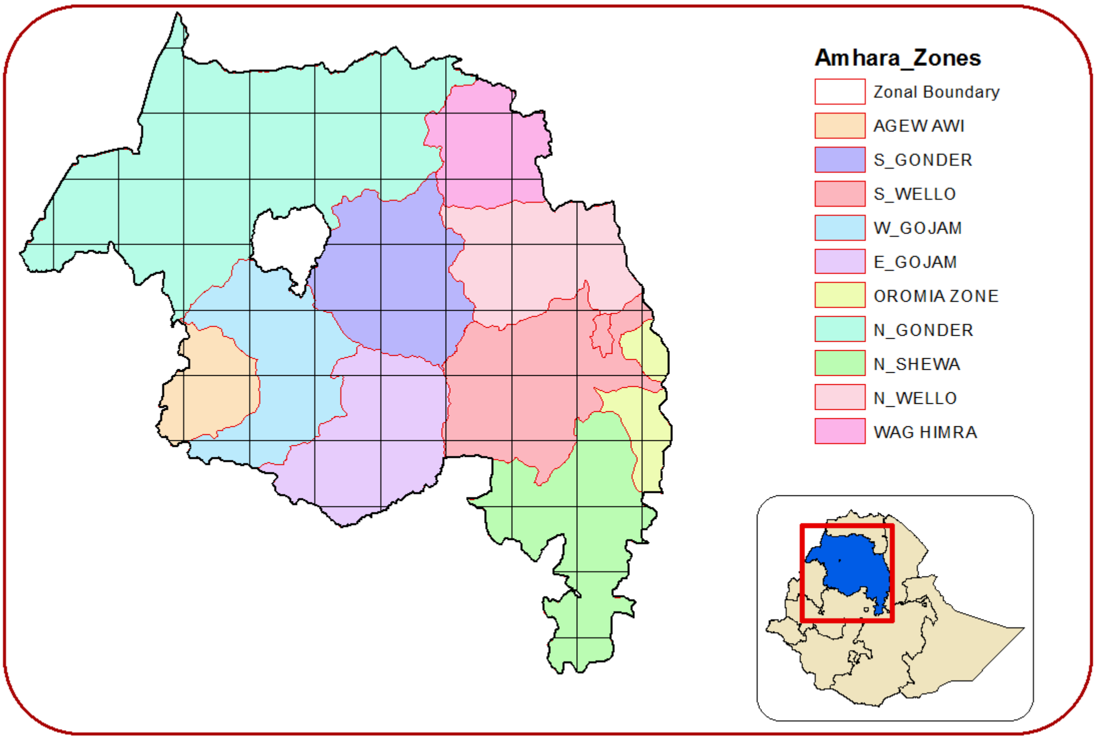

Figure 4.2: Map of crop model grid cells in Amhara region and administrative zones

All global parameters, namely those relating to crop development and water usage for wheat were adopted from (Li, 2008), except the set of parameters that were related to the thermal times of the wheat which determine the crop duration. The thermal time for the individual phenological stages required was estimated by proportionally increasing all thermal times from the mean value of the range given in (Li, 2008) by a common factor, such that the period from planting to maturity was about 120 days. The yield gap parameter (C_{YG}) was determined from a wide range of values from 0.1 to 1.0 at an interval of 0.05. Values of the parameters used for GLAM are given in Appendix A.1. These parameter values minimized root-mean-square-error (rmse) in yield for simulations of wheat yield across the Amhara region. These optimal parameters all fall within the range of the observed values.

A sensitivity analysis using the RegCM4 data showed that rmse in crop yield could not be systematically reduced across all model grid cells by changing any parameters in the crop model from the Li (2008) values. This implies that this parameter set is suitable for use with RegCM4 data. Note, however, that calibration of each grid cell individually would reduce rmse in yield, because it would result in spatially variable optimal parameters. This spatial variability in optimal parameters is in contrast to the results using the 0.5^o and 2.5^o grid in Li (2008), where the optimal parameter set was relatively constant over space. Likely reasons for the spatial variability of optimal parameters observed here include the finer spatial and temporal resolution of the RegCM4 data. For the current study, a global (Amhara-wide) wheat parameterization was retained because there is insufficient data on the spatio-temporal pattern of wheat varieties that are grown to justify local parameterization.

Model calibration follows the same procedure as Challinor et al. (2004). The sowing date and yield gap parameters are two important parameter in GLAM model. Sowing dates are determined by the local calender and condition of soil moisture. The yield gap parameter (YGP), C_{YG}, varies within a rage of 0.05-1. The optimal value is chosen by minimizing the root mean square error (RMSE) between observed and simulated yields for the whole period from 1995 to 2008. Wheat yield for Amhara region at 0.5^o scale was simulated using a calibrated YGP value for whole time period.

Chapter 5

Result and Discussion

5.1 Evaluation of the Amhara Region Summer Rainfall in RegCM4

The JJAS precipitation from the GPCP and RegCM4 are compared by averaging each across the period 1995-2008. The difference between the mean RegCM4 and mean GPCP values is an indication of systematic bias. A change in the sign of the difference is an indication of a potentially serious drift in the RegCM4 data; such a drift represents a change in the bias of the RegCM4 precipitation. Over 80% of the 46 grid cells over Amhara have the same sign.

Examining now the study period as a whole, Fig. 5.1 compares the seasonal total RegCM4 rainfall with that of the GPCP. The mean June-September RegCM rainfall is mostly higher than GPCP values, and many standard deviations are also higher. RegCM overestimates over the Southern part of the region and underestimates on edge of eastern and western part of the Region (Fig. 5.1). Overall, RegCM capture the spatial distribution rainfall in the Amhara region well.

The subseasonal variability is compared for all grid cells in Fig. 5.2. In this region , July and August are well simulated, but June and September are deficient; thus, the seasonal cycle is poorly simulated. These differences in the subseasonal variability have consequences for the model simulations in this regions.

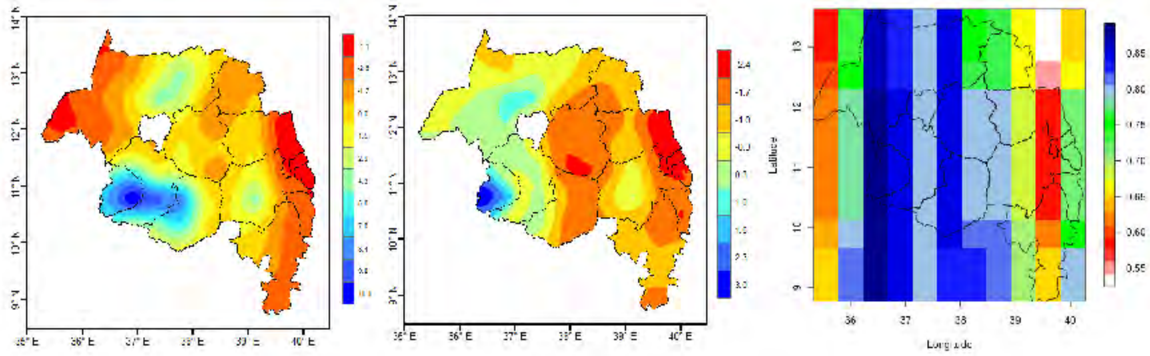

Figure 5.1: The difference between RegCM4 and GPCP data in (a) mean and (b) standard deviation of JJAS precipitation(mm/day). (c) The correlation in JJAS precipitation between the two datasets.

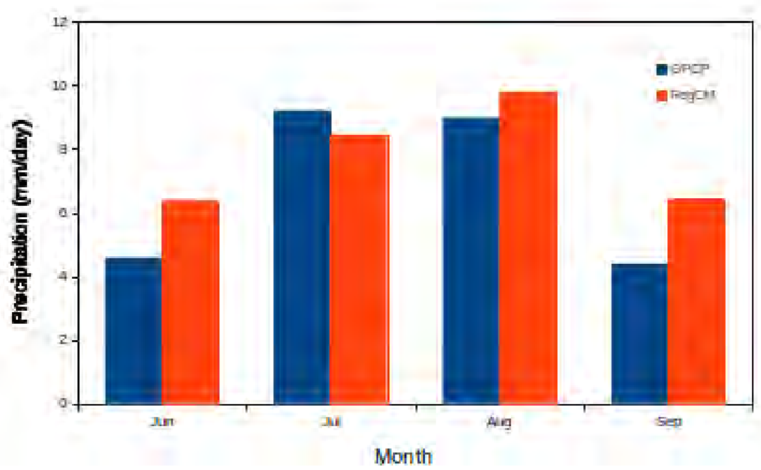

Figure 5.2: The RegCM and GPCP seasonal cycle of precipitation for Amhara region.

5.2 Crop Model Evaluation

The performance of the crop model was evaluated using three methods. First, we check the model consistency; using diagnostic output variable i.e radiation use efficiency is determined from biomass and End-of-Season Absorbed radiation, and compared to the theoretical value. The second method is comparing the observed and simulated wheat yield 0.5^o spatial scale. Finally, the observed and simulated yield time series where compared across the study period.

5.2.1 Assessment of GLAM internal consistency

The radiation use efficiency(RUE), the ratio of above ground-ground dry weight to radiation intercepted) have been widely use in differnt crop models to estimate the productivity over large spatial scale. Willson (1967) recognized that RUE reasonably constant for different crops. According to Monteith (1977) there is a linear relationship between biomass and absorbed radiation accumulation. The theoretical maximum value of RUE 2.5 $g(MJ)^{-1}$ when calculated per total absorbed radiation. For C_3 crops (whose carbon-fixation product have three carbon atoms per molecule) the measured RUE is 1.81 $g(MJ)^{-1}$.

Fig 5.3 shows the linear relationship between Biomass and the cumulative absorbed radiation for the study period. This linear relationship capture very well for GLAM yield simulation as reported Monteith (1977). The simulated RUE value is approximately 1.82gMJ^{-1}. This value agree with the reported value of 1.81 $g(MJ)^{-1}$. The correlation coefficient for the regression is 0.92.

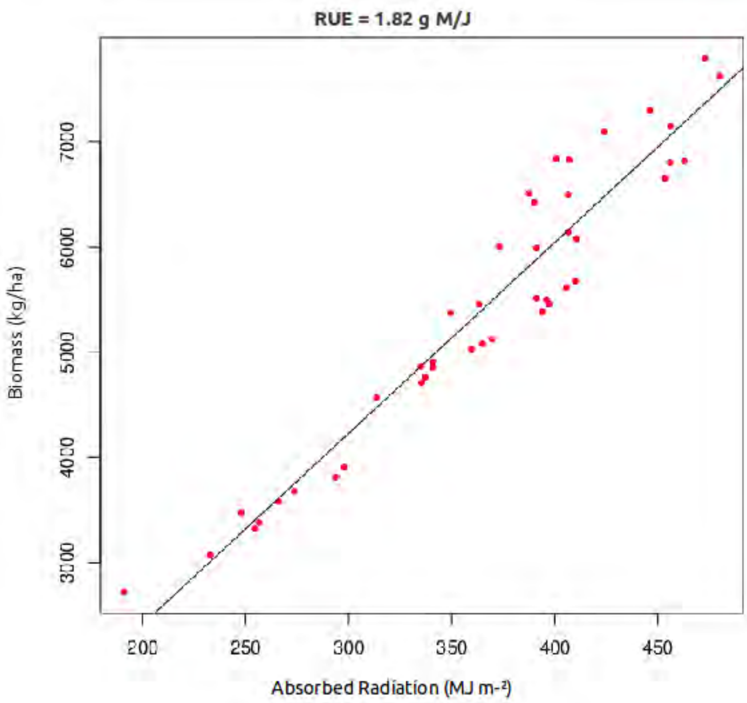

Figure 5.3: End-of-season above-ground biomass vs. cumulative absorbed radiation for Amhara region grid cells.

5.2.2 Model skill at 0.5^o Spatial Scale

The observed average wheat yield at 0.5^o scale varied from 1101 to 1917 $kgha^{-1}$, and the simulated mean yield was from 1171 to 1884 $kgha^{-1}$ between 1995 to 2008 across the Amhara region. Overall, the spatial distribution pattern of the mean yield showed a good agreement between observations and simulations(Fig 5.4). Low yields were observed in Eastern and Northeaster Amhara due to low temperature in North and Northeast Amhara .

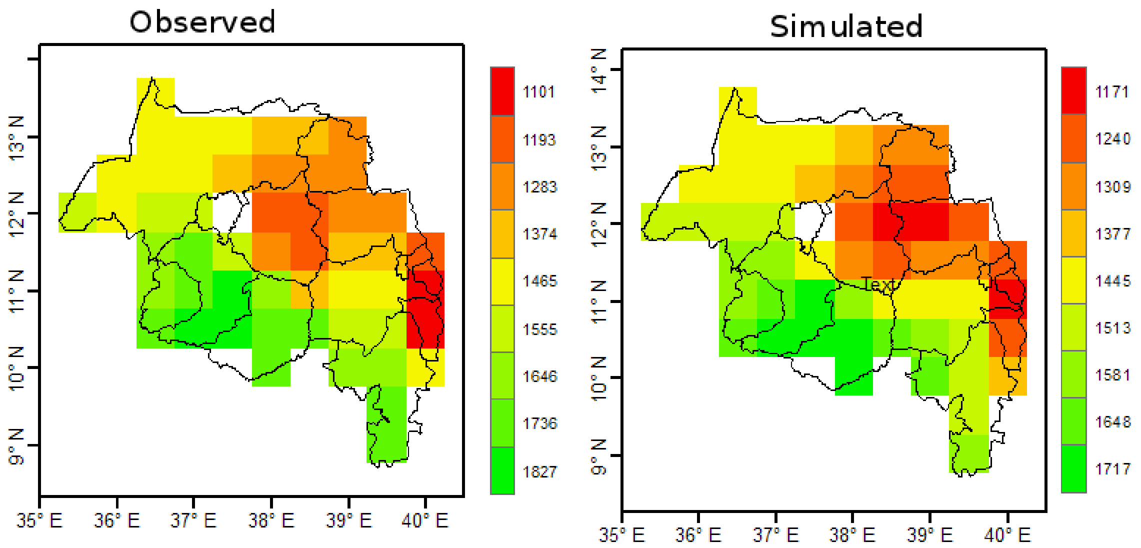

Figure 5.4: Comparison simulated and observed wheat yield$kgha^{-1}$) at 0.5^o scale from 1995-2008 in Amhara region

In most of the grid cells, the yield difference between observations and simulations was within the range of $\pm$49 $kgha^{-1}$ (Fig. 5.5a). Only in a few grid cells in southern and Eastern Amhara where yields greatly overestimated, perhaps due to the overestimations of the predicted precipitation or underestimations of the temperature in RegCM outputs (see Fig. 3.2). The simulated yields are much lower than observations in some grid cells in South and Southwest Amhara (Fig. 5.5a). Northeast Amhara is dominated by low temperature and arid or semi-humid climate, where spring wheat is mainly planted. Both the spatial and temporal variabilities of wheat yield are great partly due to the differences in availability of soil water, field management, and low temperature environment. Over all, the GLAM-Wheat model combined with RegCM4 weather data has well simulated wheat yield in 0.5^o grid cells for the period of 1995 - 2008 across the Amhara region, with the correlation of 0.56

at the 1% significant level between simulations and observations (Fig. 5.5b). This support the hypothesis that GLAM-Wheat can reasonably simulate the variability of wheat yield.

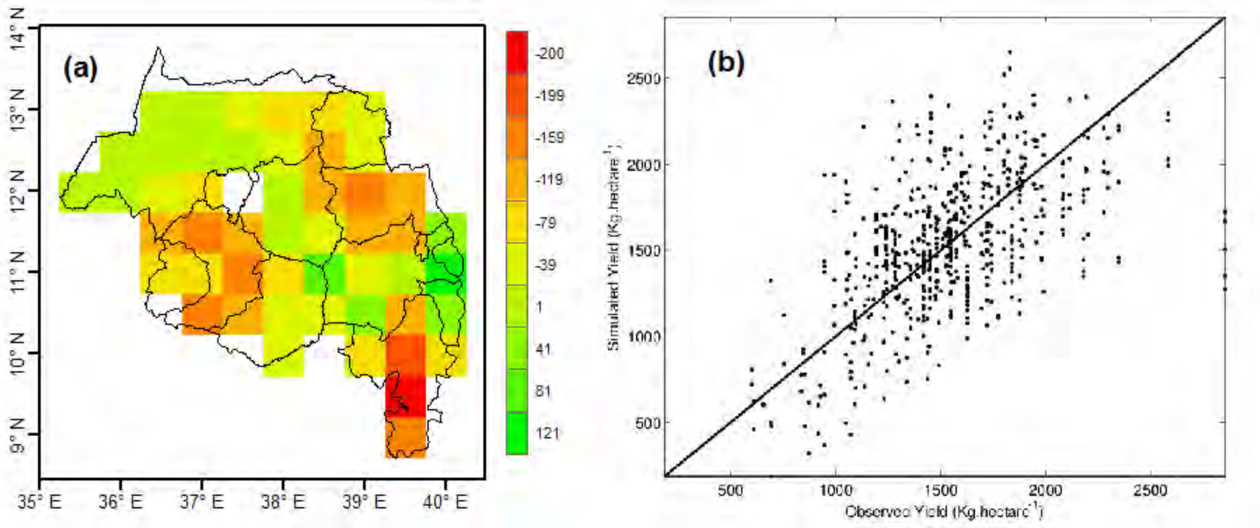

Figure 5.5: (a) Difference between simulated and observed wheat yield ($kgha^{-1}$) (b) Comparison of simulated and observed mean wheat yields (r=0.56, p ¡ 0.001) at 0.5^{o} scale from 1995 to 2008 over the Amhara region ($kgha^{-1}$)

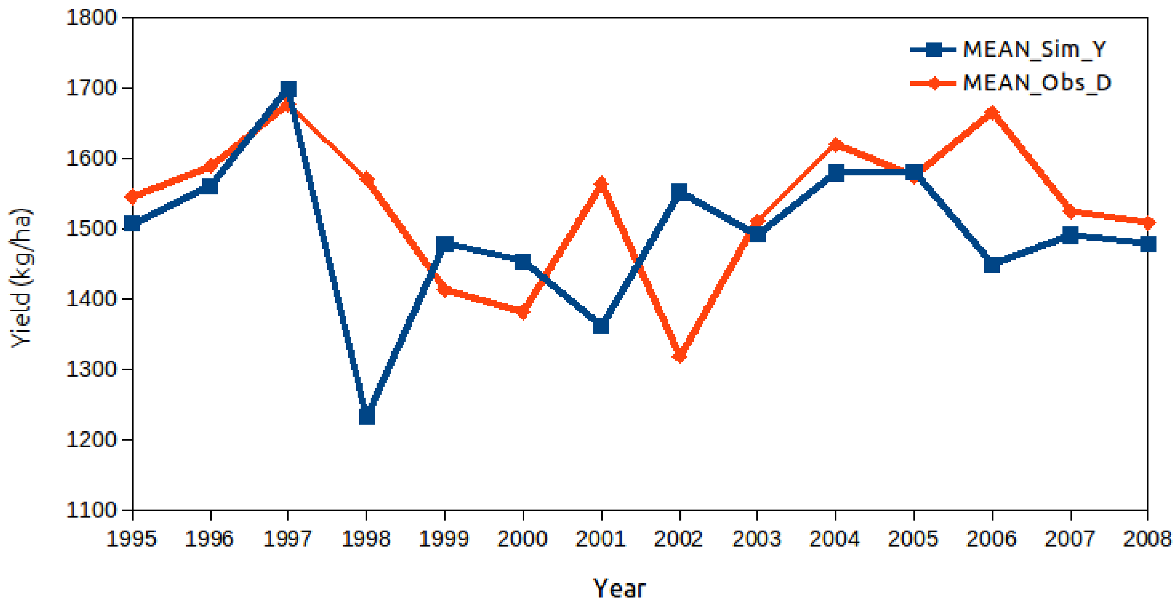

Figure 5.6: Time series of Simulated and Observed Yield, ($kgha^{-1}$)

Chapter 6

Conclusions

In this paper, we simulate summer rainfall in Ethiopia for the period of 1995-2008 to use it in impact model. Through comparing the simulation results with the GPCP precipitation data, we draw the following conclusions:

- RegCM4 has the ability to simulate the rainfall distribution and its interannual variability over Ethiopia. The main summer rainfall zone is located in Northern, Central and Western part of the country. RegCM4 can simulate the general distribution characteristics of rainfall in this regions, but the simulated rainfall overestimate over the highlands of the country. A major bias involving overestimation of rainfall over Ethiopia in the regional climate model may be carried down from its parent model (i.e., GCM).

- Statistical analysis of simulations and observations showed that RegCM4 possesses a good ability to reproduce the summer precipitation distribution in Ethiopia with the correlation of 0.79. and the coefficient of variation of rainfall for this season shows $\leq$30% in most part of the wheat producing area.

The main purpose of this thesis was to investigate the feasibility of using RegCM-4 rainfall estimates as inputs into a process-based crop model, GLAM, for crop yield forecasting in the Amhara region. The following can be inferred:

- This study has shown that downscaled data can be used to explore sources of uncertainty in yield simulation. Sufficient uncertainty exists so as to make it difficult for a modeling study on this scale to assess the accuracy of inputs, such as crop duration and the planting window. This uncertainty results in difficulty in ascribing sources of error in the input data. Because two of the simplest adaptations to climate change are changes in (total) crop duration (via the introduction of newly developed or existing cultivars) and planting date, this point is particularly relevant to climate change adaptation studies.

- The internal consistency checks that are used to ensure the performance of the crop model prove that GLAM performs magnificently. The radiation use efficiency (RUE) of the computed value is comparable to the measured one. The relationship between biomass and absorbed radiation is also found to be linear. This is in agreement with results reported in Monteith (1977).

- Correlations between simulated yields and weather agree reasonably with those observed, and this region shows the highest correlations between observed and simulated yields.

- Only in a few grid cells in southern and Eastern Amhara where yields are greatly overestimated, perhaps this observation is due to the overestimations of the predicted precipitation or underestimations of the temperature in RegCM outputs. The simulated yields are much lower than observations in some grid cells in South and Southwest Amhara. Northeast Amhara is dominated by low temperature and arid or semi-humid climate, where spring wheat is mainly planted. Both the spatial and temporal variabilities of wheat yield are high partly due to the differences in availability of soil water, field management, and low temperature environment.

Over all, the GLAM-Wheat model combined with RegCM-4 weather data has well simulated wheat yield in 0.5^o scale for the period of 1995-2008 across the Amhara region, with high correlation. This support the hypothesis that GLAM-Wheat can reasonably simulate the variability of wheat yield over Amhara region. Similar work but less comprehensive interms of evaluating the input climate data has been carried out for Southern Ethiopia which has also shown potential use of GLAM for assessment of hindicast yields and predictions of future yields.

Appendix A

Parameters for GLAM Simulation for Amhara Wheat

Listed are the parameters values used in GLAM for wheat yield simulation for the Amhara region in Ethiopia (Chapter 4). Symbol refers to the nomenclature used in (Challinor et al., 2004, Li et al., 2007).

Table A.1: New values for the parameters used in GLAM for spring and winter wheat. Values in brackets are the calibrated values.

Parameters	Description	Value
$(\partial L/\partial t)_{max}$	Maximum LAI expansion rate	0.06-0.15(0.1)
S_{cr}	Critical threshold of water stress	0.5
DLDLAI	$d(L_v)/d(LAI)$	0.5-5.0(1.0)
EFV	Extraction front velocity (cm day^{-1})	0.5-3.0(1.2)
TE	Transpiration efficiency (Pa)	3.5-6(5.0)
TEN-MAX	Maximum transpiration efficiency (g kg^{1})	5-9(6.8)
DHDT	Rate of change in harvest index	0.01
C_{YG}	Yield gap parameter	0.05-1
IEMDAY	Days from planting to emergence (days)	7-10(8)
TBFLGN	Base temperature for flowering (^oC)	0
TBGNEN	Base temperature for grain-filliing (^oC)	1
TOFLGN	Optimum temperature for flowering (^oC)	21.0 $\pm$ 1.7
TOGNEN	Optimum temperature for grain-filliing (^oC)	20.7 $\pm$ 1.4
TMFLGN	Maximum temperature for flowering (^oC)	31.0
TMGNEN	Maximum temperature for grain-filliing (^oC)	35.4 $\pm$ 2.0

Table A.2: New values for development parameters (thermal duration) used in GLAM for wheat (the length of growing season differs among different crop varieties, hence thermal duration is different)

Symbol	Name	Values	Units
T_{tt0}	Sowing to anthesis	1000-1260	^{o}C day
T_{tt1}	Anthesis to grain-filling	106-188	^{o}C day
T_{tt2}	Grain-filling to end of grain-filling	328-543	^{o}C day
T_{tt3}	End-of-grain-filling to harvest	80-100	^{o}C day

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Declaration

This thesis is my original work, has not been presented for a degree in any other University and that all the sources of material used for the thesis have been dully acknowledged.

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