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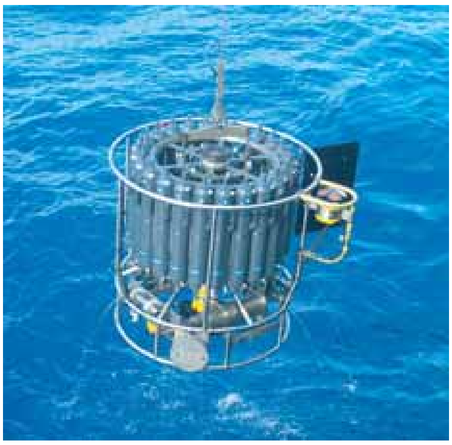
Modelling the Global Dynamics of Rain-fed and Irrigated Croplands

Maik Heistermann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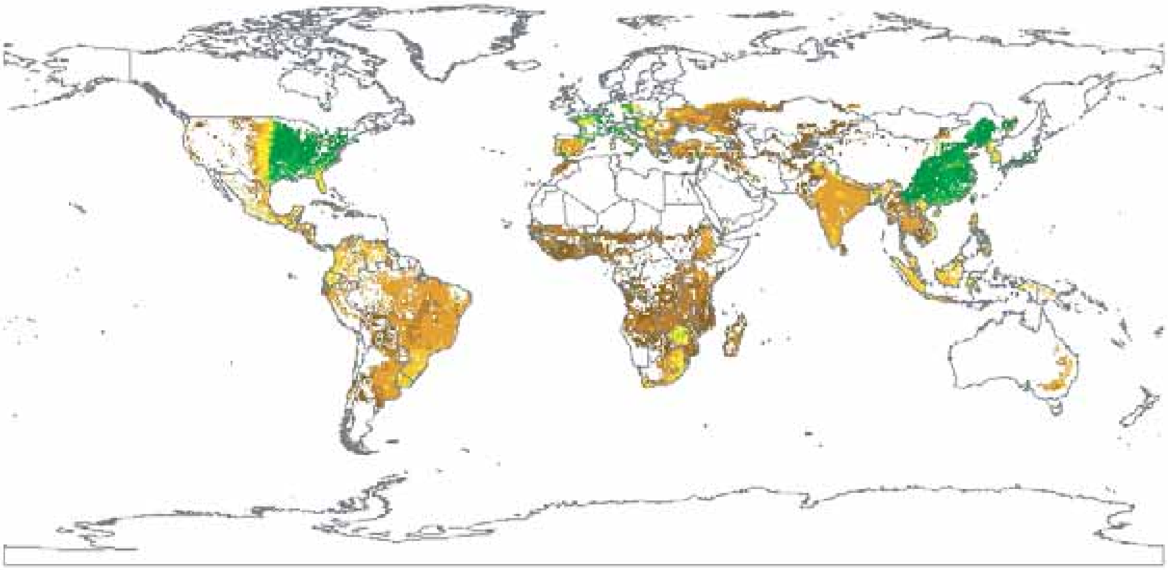
Modelling the Global Dynamics of Rain-fed and Irrigated Croplands



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To my parents

and my grandfather

Summary

Agriculture marks a major human interference to the earth's terrestrial surface. Crops "feed the world", but at the same time, their production is related to a wide range of adverse environmental impacts. Facing a growing human population together with changing food preferences, both the demand for crop products as well as the impacts of crop production will continue to rise. Modelling future changes in the extent and distribution of croplands is an important prerequisite to evaluate potential future pathways of agricultural development. This thesis is organised in accordance with the requirements to integrate the simulation of cropland changes in a new framework for global land-use modelling (LandSHIFT), with a focus on irrigated land. We identified neuralgic points for research, including i) the analysis of the current state of large scale land-use modelling, ii) the simulation of global crop yields, iii) the mapping of global crop distribution and iv) the implementation of a method to simulate the spatial distribution of irrigated land.

In order to reflect the current state of continental to global land-use modelling, we classified 18 available modelling approaches according to their integration of geographic and economic knowledge. We found that economic approaches are strong in the formalisation and quantification of drivers on the demand side while geographic approaches are rather suited to account for the supply-side limitations of land resources. Though integrated models seek to combine these strengths, core problems of global land-use modelling have not yet been resolved: this particularly includes scaling issues and the consideration of intrinsic feedbacks.

Modelling the spatial dynamics of cropland on the global scale requires two important inputs: the spatial distribution of crop specific cultivation potentials in terms of attainable yields, and a defined initial distribution of major crops. This work explicitly addresses both aspects:

First, we adopted the agro-ecosystem model DayCent to simulate the yields of major field crops on the global scale. The initial step was to develop a computational framework to operate the DayCent model on a global grid, and to compile the required input data for soil, climate and crop management with global coverage. Secondly, a procedure had to be designed to compute crop planting dates consistent with the current climate conditions. Finally, the DayCent model was parameterised and calibrated to simulate the yields of major crops on a global 30 arc minutes grid. The results show that the Daycent model is capable of reproducing the major effects of climate, soil and management on crop production. Average simulated crop yields per country agree well with FAO data ($R^2 \approx 0.66$ for wheat, rice and maize; $R^2 = 0.32$ for soybean), and spatial patterns of yields mostly correspond to observed crop distributions and sub-national census data.

To derive the global crop distribution at a defined point in time, we mapped 17 major crops plus grazing land on a spatial resolution of five arc minutes. The distribution is characteristic for the early to mid 1990ies. The mapping algorithm integrates FAO country level data with a remote sensing product and the best available sub-national census data. The resulting map was quantitatively compared against data from USDA, GIEWS and another global crop map. The comparison demonstrates consistency with existing expert knowledge, and also a general agreement with the other available crop map (if not compared on a pixel-by-pixel basis).

Using the previous results as an input, we implemented a method specifically tailored to simulate the spatial dynamics of irrigated areas in LandSHIFT. We assume that changes in irrigated areas are driven by crop demands and an exogenously specified irrigated area expansion per country. In order to assess the suitability for additional irrigated areas, we evaluated a set of landscape factors by means of Multi Criteria Analysis. As an important feature, we considered the feedback of basin level water scarcity on the potential for additional irrigated areas. Our method was successfully calibrated and validated by using a ROC metric. The actual allocation of both rain-fed and irrigated crops in each time step is realised as modified MOLA algorithm. First, the specified irrigated area expansion is allocated. The remaining demand is then fulfilled by rain-fed production. As a first application, we simulated different scenarios of irrigation expansion for the African continent. Although there is still potential to expand irrigation in large parts of Africa, we see that some regions are likely to experience severe increases in water stress. A couple of future research priorities should be addressed, particularly the issue of multiple cropping, climate variability and crop specific irrigation requirements as well as the crop specific mapping of irrigated areas.

Zusammenfassung

Landwirtschaft stellt den wohl großflächigsten und massivsten Eingriff des Menschen in die natürliche Gestaltung der Erdoberfläche dar. Feldfrüchte bilden die Haupternährungsgrundlage des Menschen, doch ihr Anbau ist gleichermaßen verantwortlich für eine Vielzahl nachteiliger Umweltauswirkungen. Angesichts einer wachsenden Weltbevölkerung mit sich ändernden Ernährungsgewohnheiten ist damit zu rechnen, dass der Bedarf an Feldfrüchten weiterhin zunimmt – ebenso wie die damit verbundenen Umweltauswirkungen. Die Modellierung der Verbreitung landwirtschaftlicher Nutzfläche ist somit ein wichtiger Schritt zur Bewertung zukünftiger Entwicklungspfade der globalen Landwirtschaft. Struktur und Inhalt dieser Arbeit orientieren sich an den wissenschaftlichen Erfordernissen zur großskaligen Simulation landwirtschaftlicher Anbauflächen sowie an den Erfordernissen zur Implementierung derartiger Methoden im Rahmen des globalen Landnutzungsmodells LandSHIFT. Ein Schwerpunkt soll dabei auf der Berücksichtigung von Bewässerungsfeldbau liegen. Entsprechend wurden folgende Forschungsaufgaben innerhalb dieser Arbeit identifiziert: i) Analyse des augenblicklichen Forschungsstands in der großskaligen Landnutzungsmodellierung; ii) die Modellierung globaler Feldfruchterträge; iii) die digitale Kartierung der globalen Verteilung wichtiger Feldfrüchte; iv) die Entwicklung und Implementierung einer Methode zur Simulation der räumlichen Dynamik bewässerter Flächen.

Um den Stand der Forschung in der kontinentalen bis globalen Landnutzungsmodellierung darzustellen, wurden 18 Modellansätze ausgewählt und klassifiziert, und zwar im Hinblick auf ihre Integration geographischer und ökonomischer Methoden. Es stellte sich heraus, dass die Stärke ökonomischer Ansätze insbesondere in der Formalisierung und Quantifizierung der nachfrageseitigen Triebkräfte liegt, wohingegen geographische Ansätze besser imstande sind, angebotsseitige Limitierungen im Hinblick auf die Verfügbarkeit geeigneter Landressourcen zu berücksichtigen. Integrierte Modelle versuchen, sich beide Stärken zunutze zumachen. Dennoch müssen diverse Kernprobleme der globalen Landnutzungsmodellierung weiterhin als ungelöst gelten. Dies gilt insbesondere für die Skalierung relevanter Prozesse und Triebkräfte, sowie für die Berücksichtigung systemimmanenter Rückkopplungs-Mechanismen.

Zwei wichtige Informationen werden zur globalen Simulation der räumlichen Dynamik landwirtschaftlicher Nutzflächen benötigt: zum einen die räumliche Verteilung der Anbaupotentiale wichtiger Feldfrüchte (bzw. die Verteilung potentieller Erträge); zum anderen eine wohldefinierte Anfangsbedingung hinsichtlich der globalen Verteilung dieser Feldfrüchte. Beide Aspekte wurden im Rahmen dieser Arbeit explizit behandelt.

Zum einen wurde das Agrarökosystemmodell DayCent zur Simulation globaler Feldfruchterträge angepasst. In einem ersten Schritt wurde ein System entwickelt, um das DayCent-Modell auf einem globalen Raster zu betreiben. Für dieses Raster wurden Eingangsdaten für Boden, Klima und Management bereitgestellt. Hinsichtlich des Managements sind die Aussaattermine ein sensitiver Parameter. Aus diesem Grund wurde ein Algorithmus zur Berechnung typischer Aussaattermine in Abhängigkeit von herrschenden Klimabedingungen entwickelt. Basierend auf diesen Vorarbeiten wurde schließlich das DayCent-Modell für die wichtigsten Feldfrüchte parametrisiert und kalibriert. Die Ergebnisse dieser Studie zeigen, dass das DayCent-Modell imstande ist, die großskaligen Effekte von Boden, Klima und Management angemessen abzubilden: Simulierte Erträge wurden auf Länderebene gemittelt und mit FAO Länderdaten verglichen ($R^2 \approx 0.66$ für Weizen, Reis und Mais; $R^2 = 0.32$ für Sojabohnen). Auch der Vergleich räumlicher Muster ergab eine akzeptable Überstimmung mit beobachteten Referenzdaten.

Zur Herleitung der globalen Verteilung wichtiger Feldfrüchte zu einem definierten Zeitpunkt wurden insgesamt 17 Feldfrüchte sowie Weideland auf einer Basisauflösung von fünf Bogenminuten kartiert. Die Karte ist repräsentativ für den Zustand Mitte der 1990er Jahre. Die verwendeten Algorithmen integrieren FAO Daten auf Länderebene mit Fernerkundungsprodukten sowie verfügbaren sub-nationalen Zensusdaten. Die darauf basierende Karte wurde mit verfügbaren Daten von USDA und GIEWS sowie mit der einzigen weiteren globalen Karte über Feldfruchtverteilung unter Zuhilfenahme quantitativer Methoden verglichen. Der Vergleich belegt die Konsistenz mit Expertenwissen aus GIEWS und USDA sowie eine gute Übereinstimmung mit dem globalen Vergleichprodukt, allerdings nur bei geringeren räumlichen Auflösungen.

Unter Einbeziehung der obigen Ergebnisse wurde eine Methode zur Simulation der räumlichen Dynamik bewässerter Flächen entwickelt und in das LandSHIFT-Modell implementiert. Zu diesem Zweck legen wir die Annahme zugrunde, dass Änderungen in der bewässerten Fläche auf Länderebene angetrieben werden, und zwar im Wesentlichen durch die Nachfrage nach Feldfrüchten sowie die maximal zulässige bewässerte Fläche pro Land (bspw. als Ausdruck einer nationalen Entwicklungsstrategie). Um die Eignung einer Rasterzelle innerhalb eines Landes für Bewässerung zu quantifizieren, wird eine Reihe von Oberflächen -und Geländeeigenschaften im Rahmen einer multikriteriellen Analyse bewertet und aggregiert. Als besonderes Bewertungskriterium wird die Verfügbarkeit von Süßwasser zur Bewässerung berücksichtigt. Da zusätzliche Bewässerung diese Verfügbarkeit reduziert, wird somit ein interner Rückkopplungsmechanismus etabliert, der dynamisch auf die Flächeneignung wirkt. Die Methode wurde erfolgreich kalibriert und unter Verwendung einer ROC-Metrik validiert. Die Allokation von Bewässerungs- und Regenfeldbau erfolgt zu jedem Zeitschritt auf Basis eines modifizierten *Multi Objective Allocation Algorithm* (MOLA): Zunächst wird die maximal zulässige bewässerte Fläche pro Land alloziert. Der verbleibende Bedarf an Feldfrüchten wird über Regenfeldbau erfüllt. In einer ersten Anwendung wurden verschiedene Szenarien für den afrikanischen Kontinent simuliert, die sich zum einen in den zugrundegelegten Ausdehnungsraten bewässerter Fläche, zum anderen in der Formulierung der oben beschriebenen Rückkopplung unterschieden. Aus der Szenarienanalyse wird ersichtlich, dass es in großen Teilen Afrikas noch ein erhebliches Potential zum Ausbau bewässerter Flächen gibt. In anderen Regionen würde die Ausdehnung von Bewässerungsfeldbau eine erhebliche Zunahme von Wasserstress zur Folge haben.

Basierend auf den Erkenntnissen der einzelnen Teilaufgaben wurde eine Auswahl besonders drängender Forschungsaufgaben für eine zukünftige Methodenverbesserung identifiziert: dazu zählen insbesondere die Berücksichtigung mehrfacher Anbauzyklen pro Jahr, die Beachtung von interannueller Klimavariabilität und feldfruchtspezifischem Bewässerungswasserbedarf sowie die Entwicklung feldfruchtspezifischer Bewässerungskarten. Insgesamt erfordert die Simulation zukünftiger Entwicklungspfade eine deutlich integriertere und konsistentere Beschreibung landwirtschaftlicher Systeme, welche auch dem sozioökonomischen Kontext gerecht wird und damit eine explizite Berücksichtigung von Vulnerabilitäten gegenüber Globalem Wandel ermöglicht.

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CHAPTER 1

General Introduction

This frieze from 2000 years B.C. depicts Egyptians using water from the Nile River for irrigation. (source: Larry W. Mays)

1.1 Croplands, Global Change, and the Earth System

Crop cultivation marks a major human interference to the earth's terrestrial surface. Today, twelve percent of the land surface are occupied by either annual or permanent crops [FAO, 2006]. Together with livestock production systems, crops provide 94 percent of the proteins and 99 percent of the calories consumed by humans [Wood et al., 2000]. In simple terms: crops are the main food source of today's human population.

Conversely, the recent decades have witnessed rising attention towards the adverse impacts of agriculture on the environment. A growing demand for food and feed products simultaneously promoted the intensification of crop management [Priess, 2006b], the unsustainable use of agricultural soils [Busch, 2006] and the expansion of croplands [Ramankutty et al., 2002]. These three processes cause a multitude of environmental impacts which, partly interlinked, affect the quality of agro-ecosystems, the integrity of natural systems, and finally, human welfare. These impacts include the export of nutrients and pesticides from agro-ecosystems, the degradation of agricultural soils (as a consequence of e.g. nutrient mining, erosion or salinisation), or the loss and fragmentation of habitats. The occurrence and prevalence of these impacts vary regionally, depending on the agro-ecological and socio-economic settings.

From the earth system's perspective, other impacts are relevant: the emission of greenhouse gases from agricultural soils as well as albedo changes through land surface conversion potentially affect the climate system [Brovkin et al., 1999]. In turn, climate change is likely to modify crop productivity in many regions of the world. Considering the hydrosphere, irrigation is only the main example of how crop cultivation can alter large scale hydrological regimes (see also 1.4). In the worst case, the interaction of atmospheric, hydrospheric, biospheric and pedospheric processes can result into system dynamics which put entire regions in jeopardy [Saiko and Zonn, 2000].

All of these processes are at the core of what is generally referred to as *Global (Environmental) Change*, which is defined as *a "wide range of changes in the physical conditions of the earth's land, oceans, and atmosphere that result from the interactions of humans and natural processes […] and affect the quality of human life and sustainable development on a worldwide scale"* [Rounsevell, 2006]. The intensity of these processes is governed by so-called *drivers* (or driving forces). From the perspective of earth system science, the primary drivers are mainly state variables of the anthroposphere, including quantities from demography, economy, society, culture and technology [Nelson, 2005]. Recently, the *Millennium Ecosystem Assessment* (MA) has provided the so far most comprehensive study to estimate both the services *currently* provided by terrestrial and marine ecosystems (including agro-ecosystems) *and* the expected changes under different *future scenarios* (i.e. assumptions on how important driving forces might change in the coming decades).

The MA impressively documented the need for integrated assessment tools in order to account for the complex interactions of the earth system's elements. Computer-based, mathematical simulation models have emerged as an indispensable tool to develop and evaluate strategies to meet food demands and other human needs on sustainable pathways. The international commitment to eradicate poverty and hunger [UN, 2000] is not negotiable. However, there is an urgent need to explore the chances and risks related to potential future pathways of agricultural development. For this purpose, integrated land-use change models have played and will play an essential role.

1.2 Croplands and Global Land-Use Modelling

As pointed out in the previous section, the assessment of cropland changes requires an integrated systems perspective. The international *Land-Use and Cover Change* (LUCC) project (a core project of IHDP and IGBP) increased our understanding of land-use change as much as our awareness of its complexity [Lambin and Geist, 2006]. Mathematical models are necessary tools to address this complexity and to promote a quantitative analysis of drivers, driver interaction, resource limitation, environmental impacts and potential feedbacks. Surely, there is no single approach that is clearly superior. Depending on the principal research questions, available models differ with respect to spatial and temporal dimensions as well as underlying theories and methodologies [Verburg et al., 2006].

Global land-use modelling approaches are still scarce, although the global scale is important for several reasons: first, many drivers and consequences of land-use change are of global extent and it is desirable to consider them in a consistent framework. Secondly, specific processes interlink locations and regions all over the globe: e.g., international trade shifts land requirements from one world region to another; or adjacent regions compete for water resources. Furthermore, land-use changes and environmental impacts are often spatially and temporally disjoint [Krausmann, 2004] and thus have to be addressed on an appropriate scale. Finally, global scale land-use models require specific methodologies that are different from smaller-scale approaches: on the one hand, strategies have to be developed to cope with data limitations. On the other hand, scaling issues have to be addressed appropriately [Veldkamp et al., 2001]: processes that are important at smaller scales such as individual decisions by local land users cannot be modelled explicitly on large scales, but their outcome has to be reflected somehow. Abstracting local land-use decisions to explain regional or global processes has to be seen as a major challenge for large-scale land-use modelling [Geist and Lambin, 2004; Lambin and Geist, 2003].

In addition to these general aspects of global land-use modelling, the inclusion of spatial cropland dynamics in a global land-use model requires specific data: to begin with, the initial condition should be known in terms of geo-referenced information about the distribution of major crops at a defined point in time. Such a crop specific characterisation is necessary because different crops have different agro-ecological and management requirements and thus have different vulnerabilities and potentials as exposed to Global Change. Furthermore, crop specific information enhances the understanding of environmental consequences [Donner and Kucharik, 2003; Lloyd and Farquhar, 1994; Still et al., 2003]. But knowledge about the initial distribution of crops is only one aspect. To model the spatial dynamics of cropland, the spatial distribution of the cultivation potential for specific crops should be known. This potential is closely related to the attainable yield under specific environmental and management conditions. Crop yield models are an adequate tool to reflect both the spatial distribution of yields *and* their changes as a result of changing climate or management. Therefore, we introduce the field of crop yield modelling in section 1.3. In addition, the potential for crop cultivation notably depends on whether the crop is to be grown under rain-fed or irrigated conditions: while rain-fed crops entirely rely on local (autochthon) rainfall, irrigated crops depend on access to allochthon water resources. In section 1.4, we address the significance and particularities of irrigated crop cultivation.

1.3 Modelling global crop yields

Agro-ecosystems are determined by their characteristic fluxes of carbon, nutrients and water. These fluxes are a function of climate, soil and management conditions and their representation in a crop growth model is a precondition to consistently assess attainable yields and the related environmental consequences of human activities. In addition, the dependence of crops on climate and soil makes them particularly vulnerable to global environmental changes such as soil degradation or climate change.

To account for these aspects of crop cultivation means to account for the underlying processes. Numerous process-based crop models have been developed during the last decades and are applied – depending on their degree of detail – from plant and plot up to regional scales [Hoogenboom et al., 1992; Jones and Kiniry, 1986; Otter-Nacke et al., 1986; Ritchie et al., 1991; Supit et al., 1994]. However, data and knowledge gaps have hindered a global application of such process models until recently. Instead, global models have so far relied on rather empirical approaches such as the Global Agro-ecological Zoning (GAEZ) model [Fischer et al., 2002]. These approaches have several drawbacks: they do not account for nutrient limitation of crop growth, nutrient dynamics in soils, leaching, erosion and water fluxes - which are all linked to agricultural production. As a result, important feedback mechanisms and links to other components of the earth system are neglected or may be inconsistent if represented by other conceptual models. The availability of improved global datasets as well as increasing computing capacities now enable the application of process-based crop and agro-ecosystem models to the global scale. This should promote consistency in addressing the complex interaction of processes at the *"crop-interface"*, such as yield distribution as a function of climate, soils and management; the export of nutrients from agro-ecosystems; green water fluxes; or greenhouse gas emissions.

1.4 Land-water linkages: the significance of irrigated croplands

The linkages between agricultural land use and the hydrosphere are manifold [see Geist, 2006, for an overview]. However, the role of irrigated crop cultivation has attracted particular attention: today, irrigated land accounts for only 20 % of the total arable area in developing countries. But as a result of higher yields and more frequent harvests, it accounts for 40 % of the crop production and close to 60 % of the cereal production [FAO, 2002]. On the other hand, irrigated agriculture is by far the most important water user in the world: it is responsible for over 70 % of all water withdrawn for human use [Shiklomanov, 2000]. Environmental impacts of irrigation include the salinization and water-logging of soils, the pollution of surface and groundwater resources [Chhabra et al., 2006] or even large scale desertification processes [Saiko and Zonn, 2000] (see Trout [2000] for an overview). Globally, irrigated agriculture almost doubled within the last 40 years and is expected to expand by another 40 percent within the next 30 years [FAO, 2002].

In contrast to the significance of the land-water linkage through irrigation, dynamic changes of irrigated areas have so far been ignored in large scale models of land-use change. To achieve such an explicit consideration, questions have to be addressed concerning the specific drivers of irrigation expansion, the spatial determinants of large scale irrigation patterns (e.g. adequate soil and terrain conditions and access to water resources), and the linkages to the hydrological cycle. The latter includes both the availability of freshwater for irrigation and the extent of consumptive water use by irrigation. It is obvious that both aspects cannot be separated since the consumption of freshwater directly implies a reduction of water available for additional irrigation. Accounting for this dynamic relationship has to be regarded as a major challenge for the explicit consideration of irrigated croplands in a large scale land-use model.

1.5 The LandSHIFT modelling framework

LandSHIFT is a framework to model continental to global land-use changes and is currently being developed at the Center for Environmental Systems Research (University of Kassel). The acronym stands for *Land Simulation to Harmonize and Integrate Freshwater and the Terrestrial Environment*. Its general structure has already been outlined in several contributions [Alcamo and Schaldach, 2006; Schaldach et al., 2006].

The guiding principle of LandSHIFT is to integrate drivers of land-use change on a country level in order to simulate changes in the spatial distribution of land use on a global five arc minutes grid. Drivers of change include demand and supply side factors, e.g. demands for settlement area, food crops, livestock, timber or energy crops as well as changes in climate, freshwater availability or agricultural management and technology. Land use and cover types comprise a set of major crop types (irrigated and rain-fed), grazing land, urban land and a set of “natural” land cover types such as forests, shrub lands or deserts. Each grid cell embodies a set of production functions which contribute to fulfil a demand in case of a particular cell being allocated to a specific land-use type. The allocation is governed by a preference ranking of grid cells. The preference level of each grid cell for a particular land-use type (e.g. a specific crop) is computed by means of Multi-Criteria-Analysis [Eastman et al., 1995]. While inter-sectoral competition (e.g. between settlements and cropland) is addressed by defining allocation hierarchies, intra-sectoral competition (e.g. between individual crop types) is dealt with on the basis of a Multi Objective Land Allocation Algorithm [Eastman et al., 1995].

A distinctive feature of the LandSHIFT model is that it promotes an integrated analysis of drivers of land-use change, but at the same time adheres to a strictly modular and transparent structure which clearly separates between different land-intensive sectors. This allows us to consider specific knowledge of land-use processes for every individual sector. In the following section, we will present modularised objectives and tasks which are oriented alongside the requirements to simulate cropland dynamics in the LandSHIFT model.

1.6 Objectives, methodologies and structure of this thesis

In the previous sections, we highlighted the scientific issues addressed in this work: the significance of croplands from the perspective of Earth System Science and Global Change; the need to analyse cropland changes in the context of global land-use models; the specific need to consider irrigated crop cultivation for such an analysis; and the required input data to allow such an analysis in terms of an initial crop distribution and the simulation of crop productivity. The guiding principle of this thesis is to integrate over these requirements by developing and providing spatial data and methodologies which are needed to simulate large scale changes in cropland, particularly irrigated cropland. This thesis does not address the entire complex of cropland simulation, but rather aims for selected, neuralgic interfaces. The data and methodologies presented here are intended to stand for themselves, but are also designed to meet the implementation requirements of the LandSHIFT modelling framework (see section 1.5). Thus, we identified the following objectives and tasks:

a) Screening available methodologies in large scale land-use modelling

Although various reviews of land-use models exist, none has ever specifically analysed available approaches for continental to global scales. In the second paragraph of 1.2, we already pointed out some particularities of modelling land-use change on these scales. The need to address these particularities is contrasted by the scarcity of available approaches. This part of the thesis has the objective to *provide an overview of land-use modelling approaches at the continental to global scale and to identify their major achievements, deficits and potentials*.

b) Modelling global crop productivity

Based on the requirements formulated in section 1.3, the next objective is to *develop a framework for the process-based simulation of global crop yields*. So far, only one process-based model (EPIC) has been applied to the global scale [Tan and Shibasaki, 2003], which does not explicitly account for nutrient management, either. Our framework is based on the Daycent model [Parton et al., 2001], which is the daily time step version of the Century model [Parton et al., 1988]. Both models have already been tested for a number of different climatic regions throughout the world [Kelly et al., 1997; Motavalli et al., 1994; Silver et al., 2000]. We emphasize the ecosystem aspect in order to provide a consistent tool which also allows the analysis of environmental consequences of crop cultivation. The DayCent model accounts for relevant processes like biomass production, trace gas emissions, carbon and nutrient dynamics, water fluxes as well as water and nutrient management. Stehfest [2005] has already applied this framework in order to assess the contribution of crop production to global N_2O-emissions. In the specific context of *this thesis*, the development of a global crop yield model mainly serves to provide local (i.e. cell based) production functions for major annual crops to the global modelling framework LandSHIFT.

c) Investigating the global distribution of major crops

As already pointed out in section 1.2, the knowledge of an initial crop distribution pattern is a prerequisite to model *changes* in the spatial distribution of croplands. To date, only one dataset is available which characterises the distribution of major crops at a defined point in time [Leff et al., 2004]. Unfortunately, this dataset has three major drawbacks with respect to its application in the LandSHIFT framework: first, the applied methodology does not enforce consistency with data reported by FAOSTAT. This is an important prerequisite for the applicability in the LandSHIFT framework since the latter employs FAOSTAT country level data. Second, the LandSHIFT model employs the concept of *dominant land use types*, meaning that only one crop type is allowed per grid cell [see Schaldach et al., 2006]. In contrast, the available map by Leff et al. allows fractions of 17 major crops per grid cell. And third, Leff et al. [2004] do not employ all available information sources, particularly on the sub-national level. Consequently, our next objective is to *derive a map of global crop distribution at a defined point in time* which meets these requirements and combines the best available data in a consistent and efficient mapping algorithm.

d) Modelling the spatial dynamics of irrigated croplands

The final objective of this thesis goes into the research needs being expressed in section 1.4: this is the *development and implementation of an approach to simulate the large scale spatial distribution of irrigated areas*. No large scale land-use model has ever explicitly addressed the spatial dynamics of irrigated areas and the related land-water linkages. Our general methodology is based on the implementation of the cropland module of LandSHIFT as presented by Schaldach et al. [2006]. This implies the application of Multi-Criteria-Analysis in order to assess the suitability of land for irrigation, and a modification of the Multi-Objective-Land-Allocation algorithm in order to consistently consider irrigated and rain-fed crops. Our methodology also for the first time addresses the dynamic interaction between irrigation expansion and water limitation. For this purpose, we use river basin data of freshwater availability and consumption as provided by the WaterGAP model [Alcamo et al., 2003]. The entire methodology is applied in an exemplary scenario analysis for the African continent which explores different trends of irrigation expansion and different formulations of water limitation concerning irrigation expansion.

This thesis is structured according to these objectives and their methodological requirements. All chapters are composed as stand-alone sections which are comprehensible in themselves. However, technically and scientifically, chapters 2-4 are prerequisites for the implementation of the methodologies and applications described in chapter 5.

Chapter 2 sets the scene by reviewing the current state-of-the-art in large scale land-use modelling. Major achievements, deficits and potentials of existing continental to global scale land-use modelling approaches are identified by contrasting current knowledge on land-use change processes and its implementation in models.

Chapter 3 documents the adaptation of the Daycent model to simulate yields of wheat, rice, maize and soybean, including the calculation of global planting dates. Simulation results are tested against national production data obtained from the FAO. Simulation results for additional crop types (potato, cassava, tropical cereals, pulses) are presented in appendix A.

Chapter 4 deals with the issue of mapping the global distribution of major crops. We discuss input data and mapping methodologies and finally compare our product against other available sources.

Chapter 5 introduces an approach to simulate changes in irrigated cropland within the LandSHIFT framework. This chapter also integrates over much of the data, methodologies and insights provided in the previous chapters.

C*hapter 6* concludes by summarizing and evaluating the findings of chapter 2-5 in the context of large scale land-use modelling in order to identify priorities for future research.

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CHAPTER 2

A review of continental to global scale land-use modelling[a]

Summary

In this review we identify major achievements, deficits and potentials of existing continental to global scale land-use modelling approaches by contrasting current knowledge on land-use change processes and its implementation in models. To compare the 18 selected modelling approaches and their applications, we use the integration of geographic and economic modelling approaches as a guiding principle. Geographic models focus on the development of spatial patterns of land-use types by analysing land suitability and spatial interaction. Beyond, they add information about fundamental constraints on the supply side. Economic models focus on drivers of land-use change on the demand side, starting out from certain preferences, motivations, market and population structures. Integrated models seek to combine the strengths of both approaches in order to make up for their intrinsic deficits and to assess the feedbacks between terrestrial environment and the global economy. Important aspects in continental to global modelling of land use are being addressed by the reviewed models, but up to now for some of these issues no satisfying solutions have been found: this applies e.g. to soil degradation, the availability of freshwater resources and the interactions between land scarcity and intensification of land use.

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[a] based on a cooperation with Christoph Müller (PIK, Potsdam) and Kerstin Ronneberger (MPI-Met, Hamburg)

2.1 Introduction

Land use[b] is a crucial link between human activities and the natural environment. Large parts of the terrestrial land surface are used for agriculture, forestry, settlements and infrastructure. This has vast effects on the natural environment. Land use is the most important factor influencing biodiversity at the global scale [Sala et al., 2000]. Global biogeochemical cycles [McGuire et al., 2001], freshwater availability [Rosegrant et al., 2002a] and climate [Brovkin et al., 1999] are influenced by land use. Closing the feedback loop, land use itself is strongly determined by environmental conditions. Climate [Mendelsohn and Dinar, 1999] and soil quality affect land-use decisions. For example, they strongly influence the suitability of land for specific crops and thus affect agricultural and biomass production [Wolf et al., 2003].

Given the importance of land use, it is essential to understand how land-use patterns evolve and why. Land-use models are needed to analyse the complex structure of linkages and feedbacks and to determine the relevance of drivers. They are used to project how much land is used where and for what purpose under different boundary conditions, supporting the analysis of drivers and processes as well as land-use and policy decisions. Based on this, we define *land-use model* as a tool to compute the change of area allocated to at least one specific land-use type.

The importance of land-use models is reflected in the increasing emergence of different modelling approaches and applications. Existing reviews try to structure this abundance by focusing on specific types of land-use changes (e.g. intensification, deforestation), specific modelling concepts (e.g. trade models) or by the development of classification systems. Irwin and Geoghegan [2001] classify models according to their degree of spatial explicitness and economic rationale. In a similar, but more elaborated approach, Briassoulis [2000] applies the criterion of *modelling tradition* in order to distinguish *statistical/econometric, spatial interaction, optimisation* and *integrated models* (defining *integration* in terms of consideration of "the interactions, relationships, and linkages between two or more components of a spatial system"). This resembles the approach of Lambin et al. [2000] (and also Veldkamp and Lambin [2001]) who evaluate models concerning to their ability to reproduce and predict intensification processes. They classify models as *stochastic*, *empirical-statistical*, *optimisation, dynamic/process-based* and, again, *integrated* approaches where *integrated* refers to a combination of the other categories. Agarwal et al.[2002] compare different approaches to deal with scale and complexity of time, space and human decision-making. Verburg et al. [2004] apply six different criteria, e.g. *cross-scale dynamics, driving forces, spatial interaction,* and *level of integration*, Li et al. [2002] add *cross-sectoral integration, feedbacks, extreme events,* and *autonomous adaptation*. Angelsen and Kaimowitz [1999] provide a meta-analysis of 140 economic-based deforestation models. Van Tongeren et al. [2001], and similarly Balkhausen and Banse [2004] focus on global agricultural trade models.

In this review, we focus on the state-of-the-art in *continental to global* land-use modelling. Global land-use modelling approaches are scarce, although the global scale is important for several reasons: First, many important drivers and consequences of land-use change are of global extent

[b] We define land use as the "total of arrangement, activities and inputs that people undertake in a certain land cover type" while "land cover is the observed physical and biological cover of the earth's land, as vegetation or man-made features" [FAO and UNEP, 1999].

and it is desirable to consider them in a consistent global framework. Secondly, specific processes interlink locations and regions all over the globe: e.g., international trade shifts land requirements from one world region to another, adjacent regions compete for water resources. Furthermore, land-use changes and environmental impacts are often spatially and temporally disjoint [Krausmann, 2004] and thus have to be addressed on an appropriate scale. We focus on land-use models of continental to global scale because these demand specific methodologies that are different from smaller-scale approaches: on the one hand, strategies have to be developed to cope with data limitations. On the other hand, scaling issues have to be addressed appropriately [Veldkamp et al., 2001]: processes that are important at smaller scales such as individual decisions by local land users cannot be modelled explicitly on large scales, but their outcome has to be somehow reflected. Abstracting local land-use decision-making to explain regional or global processes has to be seen as a major challenge for large-scale land-use modelling. Potential problems in this context are e.g. discussed by Lambin and Geist [2003], and Geist and Lambin [2004].

Our objective is to provide an overview of land-use modelling *approaches* at the continental to global scale and to identify major achievements, deficits and potentials of existing land-use models at this scale. We do this by **contrasting current knowledge on land-use change processes** (section 2.2) **and the implementation of this knowledge in current models** (section 2.3). In order to reflect the *current knowledge*, we first summarize the most important processes of global land-use change and their drivers and consequences as well as the related feedbacks (section 2.2). In order to reflect the *implementation of drivers, consequences and feedbacks into current models*, we review existing land-use modelling approaches in section 2.3. We restrict our scope to modelling approaches that are implemented as computer models, excluding purely mathematical models as well as spreadsheet and accounting approaches. In section 4, we discuss to what extend the implementation of current knowledge is limited by data availability. Based on the insights of section 2.2 (*What is known about land-use change?*), section 3.2 (*How is this knowledge implemented in global models?*) and section 2.4 (*To what extend is that implementation facilitated or hampered by data availability?*), section 2.5 identifies the major achievements, deficits and potentials in global land-use modelling, section 2.6 concludes.

For the review of modelling approaches, we take the *integration of geographic and economic approaches as a guiding principle*. In our understanding, *geographic models* allocate exogenous area or commodity demand on "suitable locations", where suitability is based on local characteristics and spatial interaction. In contrast, *economic land-use models* base the allocation of land on supply and demand of land-intensive commodities, which are both computed endogenously. With *integrated* we refer to the combination of i) economic analysis of world markets and policies in order to quantify demand and supply of land-intensive commodities and ii) the actual allocation of land use to locations based on geographic analysis. Note that we use the term "integrated" in a more narrow sense than e.g. IPCC [2001] or Parson and Fisher-Vanden [1997] in defining *Integrated Assessment* and also different from Briassoulis [2000], and Lambin et al. [2000], see above.

2.2 Processes, drivers and consequences of land-use change

Processes, drivers and consequences of land-use change are intimately linked with each other in many ways [Briassoulis, 2000]. Here, we provide a short overview only to facilitate the evaluation of modelling approaches [for more detailed reviews see Dolman et al., 2003; Meyer and Turner II, 1994]. Globally significant land-use change processes include changes in forest cover – mainly in terms of deforestation [FAO, 2003; Houghton, 1999] – and changes in agricultural areas and management [Geist and Lambin, 2002]. Changes in urban areas are of minor importance with respect to spatial extent [Grübler, 1994], although they influence global land-use change through rural-urban linkage [Clark, 1998; Delgado, 2003].

Land-use change is driven[c] by a variety of factors, both environmental and societal, which are also scale-dependant, since changes in the spatial arrangement of land use might be undetected if the resolution of analysis is too coarse or if the extent is too small. Thus, our focus on the continental to global scale has direct implications for the selection of drivers.

Concerning the natural environment, **climate** [Ogallo et al., 2000]**, freshwater availability** [FAO, 1997; Rosegrant et al., 2002a] and **soil** affect land suitability and thus land-use patterns and are impacted by land-use decisions at the same time [Duxbury et al., 1993; House et al., 2002; Lal, 2003; Saiko and Zonn, 2000; van der Veen and Otter, 2001; Zaitchik et al., 2002].

Various characteristics of societies such as their **cultural background** [Rockwell, 1994], **wealth** (income) and **lifestyle** shape the demand for land-intensive commodities [Delgado, 2003]. They are also modulated by land use as resources may be limited and typical commodities may be substituted by others. In this respect, the global context is especially important, as local and regional demands can be met in spatially disjoint regions by international trade [Dore et al., 1997; Lofdahl, 1998].

Besides shaping demand, the societal setting also determines land **management** [Campbell et al., 2000; Müller, 2004] and **political decisions** (e.g. policy intervention in developed countries and development projects in frontier regions of developing countries [Batistella, 2001; Pfaff, 1999]). Other factors include for instance land tenure regimes, the access to markets, governance and law enforcement. Such factors are known to play a decisive role in local and regional land-use change studies [Angelsen and Kaimowitz, 1999; Geist and Lambin, 2001, 2004]. However, their impact on large-scale land-use change is unexplored so far.

[c] A driver of land-use change causes – in our definition – either a change in the total area allocated to a specific land-use type or a change in spatial distribution of land-use types.

2.3 Land-use models

In the following, we will discuss not only different models but also *different versions or applications* of the *same model* (as for e.g. the IMAGE model, the CLUE model and different versions of GTAP). We did this to catch the different methodological insights to the issue of continental to global land-use modelling, e.g. by coupling the models to other models instead of using them as a stand-alone model. On the other hand, we deliberately excluded some global- to continental-scale models[d] from this review, because they do not provide additional methodological insights compared to models already considered in the review.

Our review of land-use models and their applications (table 2.1 and 2.2) is structured in three parts. We start with representatives of *geographic models*. Second, macro scale *economic models* and their relation to land issues are discussed. And third, we provide an inventory of *integrated models* (see section 2.1 for a definition of *integrated*). Note that the structures to present geographic and economic approaches differ fundamentally: for existing economic models on the global scale, land is not in the focus of interest, but was introduced mainly in order to facilitate an assessment of environmental problems such as climate change. Thus, we discuss the models along general economic modelling concepts and strategies to introduce land and land-use dynamics. In contrast, the reviewed geographic models focus on the process of land-use change itself. Thus, we show the key mechanisms to simulate this process, structured by the common approach of *empirical-statistical* vs. *rule/process-based* [see e.g. Lambin et al., 2000; Veldkamp and Lambin, 2001]: Empirical-statistical models locate land-cover changes by applying multivariate regression techniques to relate historical land-use changes to spatial characteristics and other potential drivers. In contrast, rule/process-based models imitate processes and often address the interaction of components forming a system [Lambin et al., 2000].

2.3.1 Geographic land-use models

Spatially explicit modelling is applied in many disciplines, including both natural and social sciences. However, analysing the spatial determinants of land use is at the core of geographic science. Geographic land-use studies are mainly concerned with the properties of land, its suitability for different land-use types and its location. Promoted by the introduction of remote sensing and Geographic Information Systems, the application of simulation models boosted, but mostly on local to regional scales (see reviews in 2.1). In the following, we will concentrate on geographic models available on large spatial scales.

2.3.1.1 Empirical-statistical

The CLUE model framework [Veldkamp and Fresco, 1996] was applied and adjusted to several regional case studies, of which two are on the sub-continental scale: for China [Verburg et al., 1999b] and the Neotropics/Tropical Latin America [Wassenaar et al., in press]. The underlying assumption of the CLUE framework is that observed spatial relations between land-use types and potential explanatory factors represent currently active processes and remain valid in the future. The quantitative relationship between observed land-use distribution and spatial variables is

[d] such as e.g. in EPPA [Babiker et al., 2001] and AIM [Matsuoka et al., 2001]

derived by means of multiple regression. For this reason, the CLUE model is generally referred to as an *empirical-statistical* model. Nonetheless, statistical analysis is supplemented by a set of transition rules, which additionally control the competition between land-use types. Land-use changes are driven by estimates of national-scale area demands.

The two CLUE applications pursue different objectives and different strategies to deal with scale problems. **CLUE-China** follows a multi-scale allocation procedure. Regression analysis on the coarse resolution (96x96 km^2) is assumed to reveal general relationships between land use and its determining factors over the whole study region, while finer assessments (32x32 km^2) are to capture variability within regions and landscapes [for details see Verburg et al., 1999b].

CLUE-Neotropics focuses on the identification of deforestation hotspots caused by the expansion of pasture and cropland in the Neotropics. It is assumed that the statistical relationship between grid-based explanatory variables and the actual land-use distribution might differ between different socio-economic and agro-ecological settings. Therefore, separate regression relations are established for defined sub-regions with assumed homogeneous conditions. These sub-regions are derived by intersecting the Farming Systems Map for Latin America and the Caribbean [Dixon et al., 2001] with administrative boundaries.

In total, the CLUE approach reflects the complexity of land-use change by applying a broad range of spatial suitability factors. Particularly, it accounts for spatial interaction processes and thus for the dynamic behavior of suitability patterns. This implies the potential of changing suitability patterns to drive land-use changes. Through its multi-scale approach, CLUE is able to reveal scale-dependencies for the drivers of land-use change [Veldkamp et al., 2001]. It would thus be desirable to test this methodology for the global scale, too. However, the methodology of regression analysis does not allow for a deeper understanding of the interaction of drivers and processes, which is also acknowledged by the authors. This makes long-term projections difficult, since the empirical relationships cannot necessarily be assumed constant over long time periods. On the other hand, the empirical analysis might help in identifying key processes and thus facilitate the understanding of system behaviour.

Table 2.1: Overview of the reviewed land-use models

Modelling Framework	Literature	Temporal resolution and coverage	Spatial resolution and coverage	Main mechanism	Motivation	Classification
CLUE-China	Verburg et al. [1999a; 1999b]	1-year steps; 1990 - 2010	*Multi-scale*: (China): 96x96 km grid; 32x32 km grid; subgrid; National level (China)	Observed spatial relations are assumed to represent currently active processes; allocation of area demands based on preference maps (generated through regression analysis)	Assessing the spatial impact of national scale demand trends on the spatial distribution of land-use types	Geographic (empirical-statistical)
CLUE-Neotropics (based on CLUE-S)	Wassenaar et al. [in press] [based on Verburg et al., 2002]	1-year steps; 1990 - 2010	*Multi-scale:* (Neotropics): national level, farming systems sub-units, 3x3km; Sub-continental (Neotropics)	see CLUE-China; additionally enhanced spectrum of location factors; using spatial sub-units for regression analysis based on Farming Systems Map	Identifying deforestation hotspots due to the expansion of pasture and cropland	Geographic (empirical-statistical)
SALU	Stephenne and Lambin [2001a; 2001b]	1-year steps; 1961-1997	*Multi scale:* Sahel; country level; 2.5° lat/ 3.75° lon grid; Sub-continental (Sahel zone)	Rule-based representation of the causal chain typical for land-use change in the Sahel zone: Transition from extensive to intensive use triggered by land scarcity thresholds	Reconstructing past land cover changes for Sudano-Sahelian countries as input for GCMs	Geographic (rule-/process-based)
Syndromes	Cassel-Gintz and Petschel-Held [2000]	*no explicit representation of time*	5 min. lon/lat; Global	Not a land-use model in a strict sense; rather maps present and future susceptibility towards specific land-use changes, in this case deforestation; based on fuzzy-logic	Identifying hotspots with high disposition for current and future deforestation	Geographic (rule-/process-based)
AgLU	Sands and Leimbach [2003]	15-year steps; 1990-2095	11 regions; Global	Partial equilibrium; land share proportional to economic return of the land; joint probability distribution function for yield	Simulate land-use changes and corresponding GHG emissions to feed into integrated modelling framework	Economic

- continued on next page -

Modelling Framework	Literature	Temporal resolution and coverage	Spatial resolution and coverage	Main mechanism	Motivation	Classification
FASOM	Adams et al. [2005], McCarl [2004]	5-year steps; 2000-2100	*Multi-scale:* 11 US regions (broken down into 63 for agriculture) 28 international regions (for trade) National (USA)	Partial equilibrium; non-linear mathematical programming; endogenous modelling of management; Competition of forestry and agricultural sector for land	Studying impacts of policies, technical change, global change on agricultural and forestry sector	Economic
IMPACT	Rosegrant et al [2002b]	comparative static; 1997-2020	36 regions; Global	Partial equilibrium	Analyse the world food situation	Economic
G-cubed (Agriculture)	McKibbin and Wang [1998]	1-year step; 1993-2070	12 regions; Global	General equilibrium + macroeconomic behaviour	Exploring the impact of international and domestic stocks like trade liberalization on US agriculture	Economic
GTAPE-L	Burniaux [2002]	comparative static; base year 1997	5 regions; Global	General equilibrium + transition matrix, accounting for the history of land	Exemplify the incorporation of land /land use in GTAP; Assessing GHG mitigation policies with focus on land-use impacts	Economic
Global Timber Market Model	Sohngen et al. [1999]	1-year steps; 1990-2140	10 regions; Global	Partial equilibrium; Welfare optimisation with perfect foresight	Studying the impact of set-aside policies and future timber demand on forest structure and cover, timber markets and supply	Economic
GTAPEM	Hsin et al [2004]	comparative static; 2001-2020	7 regions; Global	General equilibrium + refined transformation structure for agricultural land + substitution possibility among primary and intermediate inputs	Improve the representation of the agricultural market	Economic
WATSIM	Kuhn [2003]	1-year steps; 2000-2010	9 regions; Global	Partial equilibrium + quasi dynamic price expectations	Study the influence of trade policy on agricultural sector	Economic

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Modelling Framework	Literature	Temporal resolution and coverage	Spatial resolution and coverage	Main mechanism	Motivation	Classification
IMAGE Land Cover Module	Alcamo et al. [1998]	1-year steps; 1970 - 2100	*Multi-scale*: 13 world regions, 0.5° grid, subgrid; Global	"Agricultural Economy Model" calculates demands for agricultural and forest products; land is allocated on a rule-based preference ranking	Integrated assessment of Global Change	Integrated
IFPSIM-EPIC	Tan and Shibasaki [2003], Tan et al. [2003]	not documented	*Multi-scale*: 32 world regions, 0.1° grid level; Global	Land productivity (based on EPIC) and crop prices (based on IFPSIM) are assumed to be major determinants of agricultural land use decisions	Analysing the relation between land-use patterns and global agricultural markets	Integrated
ACCELERATES	Rounsevell et al. [2003]	2000-2050; comparative static	*Multi-scale:* Countries; soil mapping units, NUTS2; Europe	Calculation of optimal crop combinations on spatial sub-units; assumes generic farmers who maximize their long term profits	Assess the vulnerability of European managed ecosystems to environmental change	Integrated
GTAP-LEI/ IMAGE coupling within EURURALIS	Klijn et al. [2005]; van Meijl et al. [2006]	10-year steps; 2001-2030	*Multi-scale:* national level, sub-national level (NUTS2), grid level; Global with focus on EU15	Coupling of a variant of GTAPEM (GTAP-LEI) and IMAGE Using management factor and food & feed production to update IMAGE and yield and livestock conversion factor to modify production in GTAP-LEI	Assessing impact of different policies on land use in Europe	Integrated
LUC China	Fischer and Sun [2001]; Hubacek and Sun [2001]	so far quasi static; 1992 – 2025	*Multi-scale*: 8 economic regions, 5x5 km grid; National (China)	Combining AEZ assessment, extended I/O-analysis and scenario analysis to develop a spatially explicit production function for a CGE model	Analysing alternative policy scenarios	Integrated
FARM	Darwin et al. [1996]	comparative static; 1990-2090	*Multi-scale*: 8 regions, 0.5° lon/lat; Global	General equilibrium + land and water as primary inputs (imperfectly substitutable) in all sectors; AEZs defined by spatial explicit environmental data	Integrating explicit land and water assessment into CGE, environmental focus on climate change	Integrated

2.3.1.2 *Rule-based/process-based*

The **SALU** model [Stephenne and Lambin, 2001a, 2001b, 2004] is a zero-dimensional model designed to capture the characteristic processes in the Sahel Zone. It has been applied by [Stephenne and Lambin, 2001a, 2001b] in order to simulate spatially explicit changes of land use on a very coarse resolution (by dividing the Sahel region into eight independent sub-regions). It provides an appealingly simple approach to endogenously deal with agricultural intensification by focusing on a sequence of agricultural land-use changes not only typical for the Sahelian region: agricultural expansion at the most extensive technological level is followed by agricultural intensification once a land threshold is reached. Exogenous drivers are human and livestock population, rainfall variability and cereal imports. In Sahelian agriculture, intensification mainly takes place as a shortening of the fallow cycle, compensated by additional inputs such as labour and fertilizer, and by the expansion of cropland at the cost of extensive pasture (nomadic grazing). This results in the sedentarisation of livestock and overgrazing of remaining pastures (desertification).

This causal chain was recognized as also being relevant in other poorly developed parts of the world [Cassel-Gintz et al., 1997], which inspired the **syndromes concept.** Petschel-Held et al. [1999] define a syndrome of global change as a “non-sustainable pattern of civilization-nature interaction”. Cassel-Gintz and Petschel-Held [2000] applied the syndromes concept to provide global-scale patterns for the occurrence of and susceptibility to deforestation. Deforestation in this context is seen as a consequence of the *Overexploitation Syndrome*, the *Sahel Syndrome* and the *Dust-Bowl Syndrome* [Cassel-Gintz et al., 1997; Lüdeke et al., 1999]. The syndromes approach does not simulate the area allocated to specific land-use types and thus does not fit into our general definition of land-use models (see 2.1). Instead, it provides spatially explicit information about present and future susceptibility towards specific *land-use changes*. For this purpose, it distinguishes between current *intensity* of a syndrome and future *disposition* towards a syndrome. Methodologically, it combines spatially explicit and quantitative data sets with qualitative reasoning by applying the concepts of fuzzy logic. The procedure also accounts for typical tandems and causal chains by considering that a high current intensity of one syndrome (e.g. the Overexploitation Syndrome) together with a high future disposition for another syndrome (e.g. the Sahel Syndrome) might promote deforestation. Thus, the syndromes approach provides information where specific land-use changes might occur. This could basically be integrated into a quantitative framework in order to model actual land-use changes.

2.3.2 Economic land-use models

Studies of land use and land-use changes have a long history in economic theory. Strictly speaking, (agricultural) land-use studies are the origin of economic science. However, the perception of *land* in mainstream economics has changed tremendously from the only source of "real" production (Physiocrats) to just another primary factor [neoclassical theory, Hubacek and van den Bergh, 2002]. Considerations explicitly including land are now treated in specific economic sub-disciplines that are interested in the land-intensive sector such as *Agricultural and Land Economics*, *Environmental and Resource Economics* and, more recently, *New Economic Geography*.

In recent years, the rising interest in science-based assessment and treatment of environmental problems has created a new incentive to reintroduce land into standard economic models as a direct link between economy and environment. In the following, we are introducing models that are examples of the latter tendency. All of them include additional details in their land-use sectors to study the impact of environmental changes on future economic welfare. However, in a strict sense these are not land-use models. Except for the **AgLU** model [Sands and Leimbach, 2003], these models focus on changes in market structure for land-intensive goods or land-use emissions, but not on allocation of land.

Motivation and major characteristics of economic land-use models

Economic science deals with the optimal allocation of scarce resources under the assumption that profit or abstract properties such as welfare are maximized. The same focus applies to the land-use sectors. Market structures are analysed to understand land-use decisions. This mainly limits the analysis to aspects expressible in monetary terms. Most global economic land-use models are equilibrium models, aiming to explain land allocation by demand-supply structures of the land-intensive sectors. The main mechanism is to equate demand and supply under certain exogenously defined constraints. Besides data tables of in- and output of all included commodities, the most important parameters are elasticities. These describe consumer preferences and the feasibility on the producer's side by determining the impact of input changes on output or input of other commodities. On the broadest level *computable general equilibrium models* and *partial equilibrium models* can be distinguished. In *partial equilibrium models (PEM)* only a subset of the markets is modelled with explicit demand and supply functions, whereas the remaining markets are parameterised (or ignored). An important implication of this approach is the assumption that the markets of interest are negligible for the rest of the economy, since feedbacks with other sectors are largely ignored. In *computable general equilibrium models (CGE)* all markets are modelled explicitly and are assumed to be in equilibrium in every time-step. These models are based on a very rigid theoretical framework, which guarantees market closure. All money-flows are traceable through the whole economy and the structure provides the emergence of feedback effects between sectors [for more detail on CGEs see Ginsburgh and Keyzer, 1997; Hertel, 1999].

Examples of partial equilibrium models are **IMPACT** [Rosegrant et al., 2002b] and **WATSIM** [Kuhn, 2003], modelling only the agricultural sector, the **Global Timber Market Model** [Sohngen et al., 1999] describing the forestry sector, **AgLU** [Sands and Leimbach, 2003; Sands and Edmonds, 2004] and **FASOM** [Adams et al., 2005; McCarl, 2004] which include both the agricultural and forestry sectors. The high resolution of the analysed sector allows for an in-depth analysis of the respective markets or, due to its simpler market structure, an integration within an integrated modelling framework (as in the case of AgLU).

GTAPEM [Hsin et al., 2004], **GTAPE-L** [Burniaux, 2002; Burniaux and Lee, 2003] and the **G-cubed** model [McKibbin and Wang, 1998] are examples of CGEs. CGEs are often used to analyze the effects of changes in single sectors on the entire economy and vice versa. GTAPEM and GTAPE-L are used to analyse the economic impacts of greenhouse gas emissions and climate change. G-cubed was originally developed to study the impact of global environmental problems on the economy and later extended by inclusion of more detailed agricultural markets in the USA to assess the effects of trade liberalization [for more details on the PEM and CGE land-use models see Balkhausen and Banse, 2004; van Tongeren et al., 2001].

Economic land-use models differ in sectoral and regional resolution (see tables 2.1 and 2.2) and in the representation of trade and land. A realistic implementation of international trade is important to properly reproduce food and timber markets. The representation of trade in PEMs is often limited to raw or first-stage processed goods. This excludes processed food products, which account for an increasing share of the world market [van Tongeren et al., 2001]. More general, the main issue concerning international trade is whether goods are treated as homogenous or heterogeneous, distinguished by producer and origin. Assuming homogenous goods implies that neither bilateral trade flows nor intra-industrial trade can be represented appropriately [more details on trade can be found in Hertel, 1999; van Tongeren et al., 2001].

In the next section, however, we concentrate on the supply side of land-intensive goods and the treatment of land in the different models since the focus of this study lies on land allocation.

Table 2.2: Selected properties of the reviewed models. Double-headed arrows represent bidirectional feedbacks; single-headed arrows represent causal chains that lack a feedback.

Modeling Framework	Land use/cover types	Land-use change processes	Land-using Sectors	Land-using Commodities	Trade	Feedbacks/ causal chains
CLUE-China	Cropland, forest, grassland/pasture, horticulture, urban, unused	De-/Reforestation, agricultural expansion/abandonment, urban growth	-	-	-	Spatial interaction enables dynamic preference maps
CLUE-Neotropics	Cropland, forest, grassland/pasture, shrub, unused	See CLUE-China	-	-	-	See CLUE-China
SALU	Cropland, forest, grassland/pasture, unused	Deforestation, agricultural expansion/abandonment, intensification	-	-	-	Land scarcity →intensification →degradation →land scarcity
Syndromes	Forest, other	Deforestation	-	-	-	-
AgLU	-	De-/Reforestation, agricultural expansion/abandonment	Agriculture (Crops, Commercial Biomass & Livestock), Forestry	3 agricultural (one each), 1 forestry	Unilateral	Land use ↔ commodity prices; climate → land use
FASOM	-	De-/Reforestation, agricultural expansion/abandonment, intensification/ extensification	Agriculture (Crops, biofuel & livestock), Forestry	52 agricultural (24 crops, 2 biofuel, 26 livestock), 20 forestry	Unilateral	Climate → land use Land-use/management change ↔ price and cost changes
IMPACT	-	Agricultural expansion/abandonment	Agriculture (crops and livestock)	16 (6 livestock, 10 crops)	Unilateral	Land use ↔ commodity prices
G-cubed (Agriculture)	-	-	Agriculture (crops and livestock)	4 (3 crops, 1 livestock)	Bilateral	Land use ↔ commodity prices

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Modeling Framework	Land use/cover types	Land-use change processes	Land-using Sectors	Land-using Commodities	Trade	Feedbacks/ causal chains
GTAPE-L	-	De-/Reforestation, agricultural expansion/abandonment urban growth	Agriculture (crops and livestock), Forestry, Others	3 agricultural (2 crops, 1 livestock) , 1 forestry	Bilateral	Land use ↔ commodity prices
Global Timber Market Model	-	Forest-management change	Forestry	1 forestry	No trade modeled	-
GTAPEM	-	Intensification/ Disintensification	Agriculture (crops and livestock)	10 (8 crops, 2 livestock)	Bilateral	Land use ↔ commodity prices
WATSIM	-	-	Agriculture (crops and livestock)	18 (12 crops, 6 livestock)	Bilateral	Land use ↔ commodity prices
IMAGE Land Cover Module	Cropland, forest, pasture, urban, 14 biomes incl. forest	De-/Reforestation, agricultural expansion/abandonment, urban growth	Agriculture (crops and livestock), Forestry, Energy	7 food crops, 4 biofuel crops, grass and fodder, 1 forestry	Unilateral	Land use ↔ climate, land scarcity ↔ commodity demand
IFPSIM-EPIC	Agriculture	Agricultural expansion/abandonment	Agriculture	Not documented	Unilateral	Land use ↔ commodity prices
ACCELERATES	Agriculture	Agricultural expansion/abandonment	-	12 crops	-	-
GTAP-LEI/ IMAGE coupling within EURURALIS	Cropland, forest, pasture, urban, 14 biomes incl. forest	De-/Reforestation, agricultural expansion/abandonment, urban growth, intensification	Agriculture (crops and livestock)	10 (8 crops, 2 livestock)	Bilateral (GTAP-LEI), unilateral (IMAGE)	Climate ↔ Land use ↔ commodity prices, production, land scarcity ↔ yield, commodity demand, land price
LUC China	Cropland, grassland, forest	De-/Reforestation, Agricultural expansion/abandonment, urban growth	Agriculture (crops and livestock), Forestry, others	Not clearly documented	No intern. trade	Environmental conditions → future scenarios → production functions
FARM	-	De-/Reforestation, Agricultural expansion/abandonment, urban growth[1]	Agriculture (crops and livestock), Forestry, others	4 Agriculture (3 crops, 1 livestock) 1 Forestry, 8 *others*	Bilateral	Climate → land use

Land in economic models

In economic models, land is usually allocated according to its relative economic return under different uses. In CGEs, this is commonly achieved via a competitive market of land-intensive products. In G-cubed and GTAPEM land is only used for agricultural production, whereas in GTAPE-L land is also used for forestry and a so-called “others” sector, interpreted as urban land. In PEMs, area is a direct function of own and cross prices and exogenous trends (as in IMPACT and WATSIM), or the result of an optimisation of welfare and/or profit (as in the Global Timber Market Model and FASOM). In AgLU, the share of land for a certain use is proportional to its expected relative profit.

Management practices can be simulated by defining the production of land-intensive commodities as a function of primary factors such as land and labor, and intermediate inputs such as fertilizer and machinery. In order to lower parameter requirements, in CGEs intermediate inputs are commonly modelled as not substitutable to primary factors. This means e.g. that a decrease in land cannot be outbalanced by additional use of fertilizer, implying that intensification and disintensification cannot be represented endogenously [Hertel, 1999]. Of the introduced CGEs, only GTAPEM explicitly models the substitution between intermediates and primary factors. Of the introduced PEMs, the Global Timber Market Model and FASOM endogenously simulate management changes. FASOM optimises over a discrete choice set of alternative management practices, whereas the Global Timber Market Model endogenously determines a management-intensity factor.

An important aspect for the treatment of land in the production process is the heterogeneity of land. The productivity of land can vary across products, management, regions and time. The main reasons for these differences are biophysical characteristics of land, such as climate and soil. A way of introducing heterogeneity into CGEs is to loosen the common assumption that land is perfectly substitutable towards an imperfect substitutability of land between different uses and sectors. In GTAPE-L the standard GTAP model [Hertel, 1997] is modified such that land is modeled as imperfectly substitutable between the different uses. GTAPEM refined this structure by adopting the land allocation structure of the policy evaluation model [OECD, 2003], distinguishing land in the production structure of the agricultural sector even further. The disadvantage of such a non-linear treatment of land in the production functions of CGEs is that land cannot be measured in physical units of area but instead is measured in the value added to the production. This complicates the interpretation of the resulting land allocation.

In partial equilibrium models, land is commonly treated as homogenous. AgLU and FASOM are exceptions. AgLU assumes a non-linear yield distribution decreasing in land. This reflects the assumption that the most productive land is used first, whereas more and more unproductive land has to be utilized for further use, decreasing the average yield per hectare. By introducing a joint yield distribution function, where the yields of different uses are correlated, the conversion possibility from one use to another is characterized. Climate change and technological growth have been introduced by changing the yield distribution [Sands and Edmonds, 2004]. FASOM distinguishes four different classes of land mainly based on the slope of land. For timberland, ownership is also a criterion influencing land suitability. Land-allocation changes are only allowed for non-public land. Climate impacts have been studied by introducing externally estimated climate induced yield changes [Alig et al., 2003]. The so-called *Agro-Ecological Zones* (AEZ) methodology [Darwin et al., 1995; Fischer et al., 2002] allows an inclusion of environmental changes as e.g. climate change by altering the distribution of land among different classes, which are defined by the dominant climatic and biophysical characteristics. A project is close to its completion, which includes land-use and land cover data in a new version of the GTAP database, allowing for the definition of several AEZ [GTAP, 2005].

GTAPE-L captures another aspect of the land heterogeneity by introducing a so-called *land transition matrix*, tracking all land transformations among the sectors. This distinguishes land according to its history, which is quite unique in economic models. So far, however, the used transition matrix has entries solely for Europe and the USA for only two transformation processes each.

A further aspect of land, not yet touched by any of these models, is the geographic location. To properly introduce geographic location of land, the inclusion of space would be necessary. However, the required existence of an unique equilibrium in macro-economic equilibrium models prohibits the inclusion of increasing returns to scale. Without increasing returns to scale, the scale of production is not defined and thus production is distributed equally over space, hampering any notion of location [Jaeger and Tol, 2002], [for a more technical discussion on the topic see Fujita et al., 1999; Greenhut and Norman, 1995a, 1995b, 1995c; Puu, 2003; Surico, 2002].

Dynamics in economic models

Land-use change is a highly dynamic process. Land-use decisions do not only depend on current and past uses (see 2.2), but also on future expectations – especially in slow producing sectors such as the forestry sector, where long-term planning is essential. In economics, *comparative static* (equilibriums that are independent of each other), *recursive dynamic* (previous equilibriums may influence subsequent ones) and *fully dynamic* (all equilibriums for all time-steps solved simultaneously) models are commonly distinguished.

The obvious drawback of comparative static models is that they are not capable of describing any kind of time path and forward-looking behaviour. This makes these models rather inappropriate e.g. for detailed forestry studies, since this sector is governed by long-term decisions. GTAPEM and GTAPE-L are representatives of this group of models.

In recursive dynamic models, forward-looking behaviour can be implemented by assuming rational expectations based on past experience, as in WATSIM, where the economic agents expect that prices will not change. More often, however, time-dependent variables are updated exogenously. In IMPACT for example, income growth and population, as well as area- and yield growth trends are updated according to exogenous assessments.

In fully dynamic models the time path of variables is based on the assumption of an inter-temporarily optimising agent with perfect foresight. Like this, not only immediate welfare is optimised (as in recursive dynamic models) but also optimal welfare, defined over the whole period, is guaranteed. Apart from the tedious implementation and calibration of such models, their greatest deficit in respect to integrated modelling is the bi-directional notion of time, which hampers online coupling with other models. G-cubed, FASOM and the Global Timber Market Model are fully dynamic models with perfect foresight.

To appropriately model the forestry sector, the inclusion of future expectations is required, which excludes most of the CGEs. But even among the PEMs, agricultural models are more common than forestry models and very few model both sectors. AgLu and FASOM are such exceptions including both sectors in a dynamic fashion and modelling the market competition between them. FASOM simulates the competition for the land among the sectors via a perfectly competitive market. In AgLU land is distributed among forestry and agriculture proportionally to the respective expected economic return. Forward-looking behaviour is implemented by equating only one future market at each time-step to determine the expected price for timber in the harvesting year.

2.3.3 Integrated land-use models

Both economic and geographic land-use models have strengths and weaknesses. Economic equilibrium models can consistently address demand, supply and trade via price mechanisms. They are limited in accounting for supply side constraints, in reflecting the impact of demand on actual land-use change processes and in representing behaviour not related to price mechanisms. On the other hand, geographic models are strong in capturing the spatial determination of land use and in quantifying supply side constraints based on land resources. They are more flexible in describing the behaviour leading to specific allocation patterns. However, they lack the potential to treat the interplay between supply, demand and trade endogenously. In the following, we will show a selection of models and model applications which try to make up for the deficits of the disciplinary approaches. For all of these models, this is done by coupling *existing* economic optimisation models with *existing* tools for spatially explicit evaluation and allocation of land resources (except IMAGE and the IIASA LUC model for China which were rather developed from scratch). The discussed integrated models have different foci: while the **IMAGE** model, the coupled **IFPSIM/EPIC** system and the **ACCELERATES** framework rather focus on the spatially explicit allocation of land-use, the **FARM** model and the **IIASA LUC China** framework rather use spatially explicit evaluation of land resources in order to account for supply side constrains. The coupled **GTAP-LEI/IMAGE** system tries to reconcile these two foci within one framework.

The **IMAGE** model [Alcamo et al., 1994; RIVM, 2001; Zuidema et al., 1994] is a complex framework of dynamically coupled sub-models, providing an interlinked system of atmosphere, economy, land and ocean. The so-called *Terrestrial Environment System (TES)* deals with land-use and land-cover change. Within TES, the *Agricultural Economy Model* [Strengers, 2001] calculates per capita food demand, using “land-use intensities” as surrogates of food prices. Land-use intensities are the amount of land required to produce a unit of food product. Hill-shaped regional utility functions yield a utility value for a given diet. The maximization of the utility function to an optimal diet is constrained by a *land budget*. This is the area needed to produce food at preference levels, reduced by factors depending on income, average potential production and technology. Trade is introduced by exogenously prescribing self-sufficiency ratios for each of the 13 world regions. For timber demand, available forest area at a time-step is considered as surrogate for timber prices. Per capita timber demand is thus computed as a function of income and forest area. The *Land Cover Model* is based on a rule-based preference ranking of the grid cells and serves to allocate the commodity demands on a 0.5° longitude/latitude grid according to land potential. The assessment of land potential for agriculture takes into account neighbourhood to other agricultural cells, potential productivity [based on AEZ methodology, FAO, 1978], distance to water bodies and human population density. A *management factor* accounts for discrepancies between potential and actual yield. If demand in a specific time-step cannot be satisfied by suitable land, this information is fed back to the Agricultural Economy Model where the available *land budget* is reduced by a scarcity factor and a new optimal demand vector is calculated (iterative procedure).

In total, the IMAGE model has several unique features. First, it is the only model which considers the feedback between land-use change and climate change in both directions. Second, information about land scarcity from the allocation module is fed back to the economic demand module for agricultural commodities. And finally, the competition between the important land-use/cover types is included (albeit simplified and quite ad hoc).

Another approach is applied by the **land-use choice module** [Tan et al., 2003], which dynamically links the **IFPSIM** global partial equilibrium model [Oga and Yanagishima, 1996] to the **EPIC** model [Williams and Singh, 1995]. This approach accounts for the agricultural sector only and has two major characteristics: i) land-use decisions are based on price information provided from IFPSIM ii) supply is not calculated within IFPSIM but results from the land-use and yield distribution of the previous time-step. The land-use choice module is a discrete logit choice model operating on a 0.1° grid: in an utility function it considers profit for a specific crop (derived from crop yields and prices) as well as a set of socio-economic variables (population density, accessibility). Crop yields are simulated by a global version of the EPIC model [Tan and Shibasaki, 2003]. It should be noted that this approach has yet to be tested and is not applied so far. However, the implementation of a dynamic feedback between the global market of agricultural commodities and the price based decisions of local farmers would add an important aspect to endogenise market driven land-use decisions.

One objective of the **ACCELERATES** framework is to assess the change in agricultural land use on the European level, as a consequence of climate change and European policies [ACCELERATES, 2004; Rounsevell et al., 2003]. For this purpose, the **SFARMOD** farm model [Annetts and Audsley, 2002] determines the optimal crop combinations on spatial sub-units (which are based on soil mapping polygons). It emulates farmers' behaviour to maximize their long-term profits within the constraints of their situation, taking account of uncertainty in prices and yields. The constraints (water-, temperature- and nitrogen-limited crop yields, sowing and maturity days and the number of workable days) are provided by the **ROIMPEL** model [Rounsevell, 1999], an agro-climatic, process-based simulation model. Besides these constraints, the optimisation procedure is driven by exogenously determined crop prices, the cost structure for management operations and historical variability in prices and yields. Altogether, this can be seen as a bottom-up procedure where the regional land-use distribution is a result of optimised local decisions (similar to the IFPSIM/EPIC framework). However, the degree of macro-economic integration is very low. The SFARMOD model is designed to better reflect farmers' decision making than a regression model would do, however, it might be too detailed to be adapted to the global scale.

An AEZ based approach to modify crop yields according to biophysical factors is applied by the **FARM** model [Darwin et al., 1995, 1996]. The comparative static CGE is based on GTAP, but includes land as primary input to all producing sectors and water as primary input for crops, livestock and services. Water as well as land is modelled as imperfectly substitutable between the sectors and allocated in a perfect competitive market. 6 different AEZs are distinguished according to the length of growing period, which is considered as an appropriate proxy for crop suitability. The impact of climate change on crop productivity is accounted for via a shift in the water endowments and the alteration of the distribution of land across the AEZs. The FARM model was one of the first economic models to use spatially explicit environmental datasets in order to distinguish different land classes and to include the effects of climate change on land allocation. The inclusion of water and its endogenous allocation is unique among CGEs.

The coupling of GTAP-LEI (a version of the GTAPEM) and the IMAGE model within the **EURURALIS** project [Klijn et al., 2005; van Meijl et al., 2006] aims at an even further integration. In GTAP-LEI, GATPEM has been extended by a more elaborate formulation of demand in the animal feed processing sector and by a land supply curve, representing the increase of land prices when land becomes scarce. In the coupled framework, GTAP-LEI replaces the *Agricultural Economy Model* [Strengers, 2001] of IMAGE. Total crop production, as calculated by GTAP-LEI, is interpreted as demand and allocated on grid level by IMAGE as described above. In GTAP-LEI yield is determined by an exogenous trend and by the impact of endogenous management changes, which are modelled as the substitution of primary and intermediate factors (see 2.3.2). The exogenous trend is supplied by IMAGE, where changes in potential yield are modelled as a result of climate change and assumptions on technological progress. The impact of endogenous management change on yields (as modelled in GTAP-LEI) is fed back to IMAGE and used as the management factor described above. This is so far the only approach which couples a full-blown economic land-use model with a full-blown integrated assessment model. The advantage of coupling these models stands against the risk of producing redundancies and inconsistencies, as there is e.g. a land allocation mechanism in both models. As an additional part of the methodology applied within EURURALIS, the land-use patterns computed by the coupled IMAGE/GTAP-LEI models are disaggregated for Europe to a 1-km² grid using the CLUE model. Since this step is not influencing the integration of economic market analysis and the geographic assessment, we do not provide more detail on this.

The **IIASA LUC model for China** [Fischer and Sun, 2001; Hubacek and Sun, 2001] aims at a similar degree of integration, proposing a combination of an AEZ assessment, an input-output analysis and a CGE. The depth of the integration in this approach is remarkable – but it may also hamper its implementation which is still pending. The resulting CGE would not only exchange exogenous parameters with an environmental model but actually synthesize economic and geographic thinking within its theoretical foundation. Future land-use scenarios have been developed by using an extended input-output (I-O) model and spatially explicit measures of land productivity and land availability. An enhanced AEZ assessment model was utilized to provide these measures. By means of empirical estimation the agro-environmental characterization of a spatially explicit production function can be gained from the produced scenarios. This function as well as the projected I-O tables are proposed as the basis of a not yet developed CGE model.

2.4 Data availability in large-scale land-use modelling

Data for land-use modelling can be structured in four classes: (a) *Current and historical land-use data* is needed to initialise, calibrate and validate models and to analyse the determinants of spatial land-use patterns. It includes land cover characterization as well as management information such as (for agriculture) dominant crops, fertilization or irrigation; (b) *environmental data* is needed to determine environmental suitability for different land-use types mainly as a result of climate, terrain and soil conditions; (c) *socio-economic data* is needed in manifold respects: factors determining suitability for land use (such as infrastructure, access to markets), and as drivers and consequences of land use and land-use change (market structures, population and economic development, governance); (d) *scenario data* for future driving forces. These can be environmental or socio-economic, however, they are not accessible via measurement or census, but heavily rely on assumptions on future development. Scenario methodologies may range from simple ad-hoc assumptions, expert judgment or extrapolations up to sophisticated combinations of qualitative storylines with quantitative modelling [Alcamo et al., 2006]. As they are not measurable in a strict sense, scenario data will not be discussed in further detail as we do in the following for the first three categories.

2.4.1 Current and historical land-use data

Land-use data are mostly based on census, either available for entire countries [FAO, 2005] or at various sub-national resolutions. In contrast, land cover data are often derived from remote sensing (e.g. IGBPDiscover, GLC2000). However, geographic modellers are interested in the spatial patterns of *land use*: These can be derived by combining the two data sources above, making use of simple allocation algorithms [Leff et al., 2004; Ramankutty and Foley, 1998]. However, major inconsistencies between the two data sources indicate their limited quality. This deficit is substantiated by Young [1999], who fundamentally criticizes existing estimates of cultivated land and land still available for cultivation.

Another problem is the availability of spatially explicit time series of land use and cover, needed to analyse *actual changes*. Lepers et al. [2005] provide only a limited solution to that problem by geo-referencing regional studies of land-use changes, partly based on 20-year time series of AVHRR data. From that, they derive so-called “land-use change hot spots” which indicate regions with significant land use dynamics. Klein-Goldewijk [2001] and Ramankutty and Foley [1999] provide historical land-use patterns, but only by applying backward simulation on the basis of coarse historical records.

Finally, the management aspect of land-use is insufficiently reflected by available data. Data on fertilization rates is only provided on the country level which is too coarse for large countries. Data on irrigation [Siebert et al., 2002] have a higher spatial resolution, but only indicate the area equipped for irrigation (no information about irrigation intensity and irrigated crops). Other missing data comprise for example forest management and logging practices, and agricultural management aspects, such as crop-livestock integration, livestock farming with zero-grazing, planting dates, typical crop rotations and multiple cropping. A more integrated view on the different aspects of agricultural land use is provided by the farming systems concept: A farming system is characterized by similar resource bases, enterprise patterns, household livelihoods and constraints of farms within a region. Dixon et al. [2001] compiled a geo-referenced database of farming systems for developing and transition countries.

2.4.2 Environmental data

Environmental data are usually provided on a regular grid, either derived from remote sensing (as for topography), interpolation of point data (as for climate and soil data) or gridded polygon data (as for soil properties). Although environmental data are associated with large uncertainties, general data availability has to be considered as less limiting than for the other data categories. However, there are still deficits: e.g. there is a strong need for quantitative data about soil degradation going beyond the GLASOD study [Oldeman et al., 1990]. Climate data are only available on a monthly basis, forcing users to generate artificial daily values e.g. for crop modelling [Tan and Shibasaki, 2003].

2.4.3 Socio-economic data

Socio-economic data are rarely available at high resolutions. Mostly, data are provided on the national or – at best – sub-national level. Only population-count data (e.g. LandScan), which is also acquired by the help of remote sensing of city night-lights, is available at high spatial resolutions (1km x 1km). The collection of socio-economic data is more costly, more susceptible to uncertainty and of low comparability due to more intransparent and unstandardised collection methods. In addition, data quality differs between regions. Generally, economic data on prices, trade volumes, production and consumption are easier available than rather qualitative data: there are virtually no large-scale data about land tenure systems (e.g. traditional/communal vs. private), the role of subsistence farming, market access, development policies, governance, or institutional enforcement. Such information would already be useful at low spatial resolutions in order to characterize regional differences in land-use dynamics. However, the fuzziness of the variables hampers quantification and application.

2.4.4 Data integration

As can be seen from all data categories, a limited volume of raw data in terms of census, remote sensing or station measurements is increasingly processed by modelling techniques in order to derive spatially explicit data for land-use models. Processing techniques include simple allocation schemes using remote sensing or proxy data in order to derive spatial patterns from census data (e.g. Leff et al. [2004] for major crops; Siebert et al. [2002] for irrigation; Wood and Skole [1998] for deforestation). Dobson et al. [2000] apply a set of eight proxies to derive human population density (including e.g. slope, road proximity).

Moreover, more complex models provide input data to land-use models such as the global distribution of potential yields or vegetation, again being based on complex environmental data, including the output of climate models. Against this background, it is a major challenge for land-use modellers to carefully reflect on their input data and their origin in order to avoid artefacts in the analysis of land-use patterns or in calibration of model parameters. Nevertheless, the strategy to merge data from remote sensing with ground census still seems to bear large potentials to boost data availability and quality [Perz and Skole, 2003].

2.5 Major achievements, deficits and potentials

Choosing and classifying relevant modelling approaches is an ambivalent task. On the one hand our focus on *land allocation models* excluded some approaches towards an integration of economy and environment. E.g. Perez-Garcia et al. [2002] is one of the few integrated approaches, where forestry is in the focus of interest. Land and land allocation, however, is not explicitly modelled (or at least not documented). On the other hand, the differentiation into integrated or economic models was not always straightforward. FASOM, for instance, uses EPIC simulation results to include some environmental impacts for agricultural production; GTAPE-L offers a certain degree of integration by including land history, which is a spatial aspect of land; and AgLU not only accounts for certain biophysical characteristics of land, it also is a tool designed to establish a feedback loop with the integrated **Assessment of greenhouse gas emission reduction strategies** model **ICLIPS** [Toth et al., 2003]. We decided, however, that the economic basis or the contribution to the economic aspect in these models outweighs the integration aspect. Finally, our aim was to choose a set of representative approaches characterizing the current state-of-the-art. This excludes some modelling approaches which are very similar to the selected ones – though we do not claim these approaches to be irrelevant or less useful.

Each type of land-use change of major importance at the global scale (see 2.2) is covered in at least one of the reviewed models. However, not all models include all major types of land use and are – especially in the case of economic land-use models – rarely designed to primarily model land-use changes and the related processes. At the global scale, the EURURALIS framework still addresses land-use changes most explicitly while most global economic models consider land only as an input to production; Syndromes is not intended to allocate land and IFPSIM/EPIC only considers major crops. On the continental scale all the selected models or model applications have an explicit focus on land-use changes (e.g. CLUE, SALU, ACCELERATES, LUC China, FASOM). Concerning FASOM, CLUE-China and CLUE-Neotropics, the applied methodologies could basically be applied to the global scale, too, while ACCELERATES and SALU are rather tailored for regional application and LUC China is not even fully applied within China.

Concerning the reviewed geographic models land is commonly modelled as a carrier of ecosystem goods such as crops or timber. They focus on the dynamics of spatial patterns of land-use types by analysing land suitability and spatial interaction. Allocation of land use is based either on empirical-statistical evidence (CLUE) or formulated as decision rules, based on case studies and common sense (Syndromes, SALU). Empirical-statistical approaches can account for a large choice of suitability factors, spatial interaction and thus dynamic suitability patterns. Beyond, they can explicitly account for scaling issues by performing the statistical analysis on different scales and thus revealing scale dependencies of drivers. Rule-based models are based on a certain understanding of land-use decisions. Thus, they are able to reproduce causal chains (e.g. explaining intensification and degradation in the Sahel Zone), the synergetic interaction of drivers and processes or the impact of governance (Syndromes approach). However, upscaling of decision-making processes is not explicitly discussed in the reviewed modelling studies (see below).

In contrast to the geographic approach, economic models focus on drivers of land-use change on the demand side. They represent trade, which shifts land requirements from one world region to another. However, the actual impact of trade on land-use changes is rarely explicitly addressed in the reviewed studies. Land is usually implemented as a constraint in the production of land-intensive commodities and the focus is more on the outcome of land use than on its allocation. The economic competition of different uses within one sector is represented endogenously. The simulation of management changes as well as the competition among different sectors are supported by the structure of such models but seldom actually included. This strongly limits the representation of land-use change processes (see table 2). Land is often utilized in one sector only, but even the inclusion in several sectors does not guaranty a proper representation of land-use changes. FASOM and AgLU are the only economic models that provide an appropriate framework to model competition and resulting changes between two land-intensive sectors (agriculture and forestry). But as partial equilibrium models (and FASOM additionally due to its regional focus) their representation of global trade is limited. The inclusion of management changes or technological progress is hampered by the models' internal representation of the production process (see 2.3.2) and data availability. The inclusion of a production structure allowing for substitution of primary and intermediate goods in GTAPEM, however, is a first step towards a better representation of management changes in CGEs.

Current integrated land-use modelling approaches provide evidence that some of the intrinsic deficits of geographic and economic approaches can be overcome to a certain extent. Several strategies of integration can be identified: Some studies employ a land allocation scheme, which uses demand or price information from economic models to update land-use patterns in detailed environmental models (ACCELERATES, IFPSIM/EPIC). The land-use choice model in the IFPSIM/EPIC approach determines the supply side outside the trade model and thus allows for a dynamic feedback between land-use patterns and global demand. IMAGE computes demand internally without external price information. It is the only model which accounts for the feedback of land scarcity on demand although the economic demand module is theoretically weak, as also admitted by its author [Strengers, 2001].

The coupling of IMAGE and GTAP-LEI in the EURURALIS project aims to improve on this weakness. It enhances the economic foundation of the IMAGE land-use model and improves the representation of land supply in the GTAPEM version. Beyond, a first step towards a representation of the relation between land scarcity and intensification has been achieved by implementing a land supply curve in GTAP-LEI. The remaining integrated approaches focus on improving the representation of the supply side within a general equilibrium approach by considering spatially explicit environmental information: In FARM, different land types are distinguished and evaluated (AEZ methodology) whereas in IIASA LUC China the entire supply function is planned to result from environmental and economic analysis. In addition, these models also refine their land allocation mechanism. FARM for instance, includes land in all sectors, enabling competition for land[a]. Additionally, a competitive market for water is implemented, which improves the representation of management.

Despite these achievements, the full potential of integrating economic and geographic approaches seems not to be fully explored, yet. For the coupling of different modelling approaches as in the EURURALIS framework, the advantages of process detail stands against the risk of inconsistencies and redundancies. The reviewed models lack endogenous approaches to determine whether food

[a] But the comparative static setting prohibits an inclusion of planning based on foresight for the forestry sector.

demand will be satisfied rather by expansion of agricultural area than by intensification. Beyond a more detailed representation of agricultural management, including the feedback with soil and water is also needed. Irreversibly degraded soil or the exhaustion of freshwater resources are major constraints on future land use, that have not yet been tackled sufficiently by any land-use model. Admittedly, there are several models which consider irrigation and FARM even includes the competition for water among water-intensive sectors. However, water resources are not bound to environmental processes in these models, so that no feedback loop is established. Yet, it should be critically assessed whether all these issues can be addressed within one single framework or rather in related scenario storylines.

Other methodological challenges are still ahead. The problems associated with different time-scales and dynamics are often ignored. Environmental studies operate on large temporal scales of up to 100 years or even more. Studies including human behaviour are designed to operate on smaller time scales, typically ten to twenty years. Predominantly, the parameterisation of human reactions and behaviour makes long-term projections highly uncertain, as it is mainly based on current or past observations. This also holds true for the economic approach which uses motivation based theory instead of observed behaviour. The same applies for spatial scales. How can human behaviour be described at a continental to global scale? Individual behaviour cannot be simply transferred to the continental or global scale. Empirical geographic models implicitly account for scale effects by using regression techniques on the scale of application. Rule-based models have more problems in generalizing local behavioural patterns to large scales. The Syndromes approach suggests a way to base such up-scaling tasks on large-scale process patterns (called Syndromes). However, large-scale modelling studies rarely explicitly address the scaling issue. There could be some potential in combining empirical-statistical approaches with rule- or process-based settings in order to explore scale dependencies of drivers while employing explicit process description.

Moreover, the interpretation of parameters can differ tremendously among different models. An obvious example is the representation of land in CGEs as value added for the production. A simple mapping from dollars to hectares will not be sufficient to account for the different underlying interpretations.

2.6 Conclusions

Global land-use modelling approaches are scarce in spite of the importance of the global context for land-use change processes. Current approaches to continental and global land-use modelling bear the potential to model land-use dynamics but still need further efforts since land-use is rarely the primary objective of these models. The strength of economic models is the description and quantification of drivers on the demand side. They provide a structure to represent the competition among different sectors, changes in management and technology and demand shifts due to trade or policy interventions. Geographic models explicitly address information on fundamental constraints on the supply side and allow for path dependence by tracking inventories of land and their productive potential. Beyond, they are flexible and open to integrate socio-economic drivers and their synergies [Geist and Lambin, 2002; Lambin et al., 2003]. Integrated models seek to combine these strengths in order to make up for the intrinsic deficits of both approaches and thus to assess the feedbacks between terrestrial environment and global economy.

But despite the achievements and individual strengths of the selected modelling approaches, core problems of global land-use modelling have not yet been resolved. Scaling issues are rarely explicitly discussed. Models need to address several land-use types and their drivers simultaneously in order to account for their competition. Beyond, the inclusion of feedbacks between society and environment are needed and call for further efforts in integrated land-use modelling. For a new generation of integrated large-scale land-use models, a transparent structure would be desirable which clearly employs the discussed advantages of both geographic and economic modelling concepts within one consistent framework and avoids redundancies. For this purpose, suitable access points for model coupling need to be identified.

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CHAPTER 3

Simulation of global crop yields[a]

Summary

Agriculture has become a key element within the earth system as it changes global biogeochemical and water cycles, while global environmental change affects land productivity and thus future land use decisions. To address these issues and their complex interdependency in a consistent modelling approach we adapted the agro-ecosystem model DayCent for the simulation of major crops at the global scale. Based on a global compilation of environmental and management data and an algorithm to calculate global planting dates, DayCent was parameterised and calibrated to simulate global yield levels for wheat, maize, rice and soybeans. Simulation results show that the DayCent model is able to reproduce the major effects of climate, soil and management on crop production. Average simulated crop yield per country agree well with FAOSTAT yield levels ($R2 \approx 0.66$ for wheat, rice and maize; $R2 = 0.32$ for soybean) and spatial patterns of yields mostly correspond to observed crop distributions and sub-national census data.

[a] based on a cooperation with Elke Stehfest (MNP, Utrecht)

3.1 Introduction

Modelling plant growth has a tradition starting long before today's computer models. Classical works such as by Sprengel [1828], Liebig [1840] or Mitscherlich [1909] are still influential. Their core questions - *what is limiting crop growth and what is the optimal management?* - are still being addressed by modern crop models. However, the scope of crop modelling has expanded. An important new motivation for crop modelling are questions regarding the impact of climate change and increasing human population on future food security. Crop modelling has thus been applied to assess the availability of additional land for agriculture [Fischer et al., 2002; Kenny et al., 2000], to investigate the impact of climate change on future land use [Alcamo et al., 1998] or on future economic welfare [Matsuoka et al., 2001; USGCRP, 2001].

There is also a concern about the adverse environmental effects of agriculture. Water quality is affected by the export of nutrients and pesticides from agro-ecosystems, leading to eutrophication and declining biodiversity [Howarth et al., 1996; Stoate et al., 2001]. Water withdrawals for irrigation can lead to severe water stress in downstream areas [Saiko and Zonn, 2000; Zaitchik et al., 2002]. Beyond, unsustainable and inadequate management might cause severe and sometimes irreversible degradation of soil quality, e.g. in terms of nutrient mining, salinisation or compaction of soil [Oldeman et al., 1990]. Furthermore, agriculture is a major emitter of greenhouse gases and thus contributing to climate change. Duxbury [1993] estimates that agriculture accounts for 92 percent of all anthropogenic emissions of N_2O (26 percent for CO_2, 65 percent for CH_4).

The processes underlying these different aspects of crop production and its modelling are strongly interconnected and should therefore be treated within a consistent framework, as illustrated by the following examples: The potential contribution of irrigation and fertilisation to meet increasing food demands can only be assessed if the model is able to account for the processes governing nutrient and water limitation. Greenhouse gas emissions from soils can only be calculated if the nitrogen and carbon removed by crop growth are adequately considered. The same applies to problems such as nutrient mining or nutrient leaching. Donner and Kucharik [2003] have taken a first step towards such an integrated consideration of fertilizer application, crop growth and nitrate leaching in the entire Mississippi basin. Last but not least, models need to incorporate actual management in terms of fertilisation and irrigation in order to be tested against actual crop yields.

However, existing simulation models often focus on special aspects of the agricultural plant-soil system: a large number of models has been developed in order to optimise agricultural management strategies, but also to investigate the effect of climatic variability and soil hydrology on crop yields. These models employ detailed representations of plant phenology and physiology, resulting in laborious parameterisation and calibration. Examples are the CERES model family [Jones and Kiniry, 1986; Otter-Nacke et al., 1986; Ritchie et al., 1991], WOFOST [Supit et al., 1994] or CROPGRO [Hoogenboom et al., 1992]. These models have yet been applied over a wide range of scales, e.g. Eitzinger et al. [2004] applied WOFOST for lysimeter studies; regional to sub-continental modelling studies were performed with CERES [Saarikko, 2000] and WOFOST [Boogaard et al., 2002]. The EPIC model [Sharpley and Williams, 1990; Williams et al., 1984] was originally developed to study the impact of soil erosion on yields, but includes a detailed description of crop growth as well. Another group of models focuses on soil biogeochemistry and nutrient cycling, e.g. RothC [Coleman and Jenkinson, 1996; Jenkinson et al., 1991] for organic carbon turnover, CENTURY [Parton et al., 1988] for carbon, nitrogen, phosphorus and sulphur cycles, DNDC [Li et al., 1992a, 1992b] and CASA [Potter et al., 1993] for N_2O emissions, and MEM [Cao et al., 1995] for CH_4 emissions. These models pay more attention to soil processes, such as decomposition, nitrification and denitrification. However, there are efforts to improve the representation of crop growth in such models [Zhang et al., 2002]. Reviews about the general features and mechanisms of process-based crop models are e.g. provided by Tubiello and Ewert [2002] who focus on the effects of elevated CO_2 concentrations and by Lipiec [2003] who deals with crop growth, water movement and solute transport.

As pointed out, the detailed representation of processes makes parameterisation of such models a demanding task. Notorious data and knowledge gaps have yet hindered a global scale application. Instead, reduced form and rather empirical models have been developed for global scale applications, of which the Global Agroecological-Zoning (GAEZ) approach is most advanced [Fischer et al., 2002; Leemans and van den Born, 1994]. The methodology of GAEZ is based on the AEZ approach [FAO, 1978] and combines the concepts of climatic envelopes with phenological modelling and the incorporation of reduction factors for soil, terrain and climate impacts on crop yields.

Only recently, one of the above mentioned process models, EPIC, was tested on the global scale for wheat, maize, rice and soybeans [Tan and Shibasaki, 2003]. Considering the increased availability of global data on agricultural management, soils and climate, it is now possible to apply more sophisticated process models on the global scale. This will allow models to include the complex interaction of processes in the plant-soil system and to address the issues mentioned above - *climate change impact, crop production, soil degradation, greenhouse gas emissions, nutrient leaching, management impact on yields* - within a *consistent* global framework.

The objective of this study is the adaptation and application of a detailed process model, the DayCent model, to the computation of global crop production, in order to address these diverse aspects of the global agricultural systems, and to present first results of simulated global crop yields. The DayCent model, which operates at a daily time step, and the CENTURY model (monthly time steps) [Parton et al., 1988] were originally developed to investigate carbon and nitrogen dynamics in the US Great Plains, but have since then been successfully tested on several temperate [Kelly et al., 1997] and tropical sites [Motavalli et al., 1994; Silver et al., 2000]. The daily time step of DayCent allows for a more detailed consideration of soil water fluxes, plant phenology and particularly processes determining the emission of N_2O and NO. Beyond, the decision to employ the DayCent model was strongly influenced by the model's detailed representation of soil biogeochemistry, as nutrient pool dynamics strongly determine nutrient availability and thus crop yield, and also influence future land use options.

In the next section we provide an overview of the main mechanisms determining plant growth and yield formation in the DayCent model and discuss the various input data used for its application to global crop modelling, including crop parameterisation, climate and soil data as well as management information. In chapter 3.3 we present the results for planting dates and the global yield distribution of wheat, rice, maize, and soybean. The results are compared against average country data as reported by FAO and against spatial patterns derived from selected sub-national census data. In chapter 3.4, we conclude with the identification of major achievements and deficits of our approach and an outlook on improvements planned for future model versions.

3.2 Materials and Methods

3.2.1 The DayCent model

The DayCent model is a terrestrial ecosystem model designed to simulate C, N, P and S dynamics of agricultural and natural systems [Del Grosso et al., 2002; Parton et al., 1998]. It is driven by daily precipitation, maximum and minimum daily temperatures and a daily scheduling of management events. Therefore most soil processes operate on a daily scale, while plant growth is simulated weekly. The soil water sub-model, which is part of the land surface processes representation [Parton et al., 1998] simulates soil water content and water fluxes (i.e., runoff, leaching, evaporation, and plant transpiration) for user-defined soil layers. The soil organic matter (SOM) sub-model calculates decomposition for dead plant material and three SOM pools with different turnover times. Nitrification, denitrification, and N trace gas fluxes are tightly associated with the SOM sub-model. Both sub-models are described in the literature [Century-Manual, 2005], therefore we will only describe their impacts on plant growth and the plant growth sub-model itself in more detail.

Potential production is calculated as a function of solar insolation, biomass, temperature (using a crop specific optimum temperature growth function) and the constant crop-specific energy-biomass conversion factor “prdx”. The prdx reflects the genetic potential of crop type and variety, but also management conditions like row distance, and is the main plant growth calibration parameter. The potential production is reduced by water stress as illustrated in Figure 3.1a. If the ratio between available water and potential evapotranspiration (calculated according to Penman-Monteith [FAO, 1998]) drops below an upper threshold, potential production is linearly reduced down to a lower threshold of available water to PET, below which no production is possible. This water-limited potential production is further limited by the availability of nitrogen for meeting the C/N ratios of new biomass. These C/N ratios depend on N availability, and increase during crop growth, as a function of effective temperature sum as shown in Figure 3.1b. It is assumed that the maximum C/N ratios are reached at the onset of grain-fill. The mineral nitrogen available for growth can be supplied from fertilizer addition of nitrate or ammonium, nitrogen fixation, from mineralisation of the soil organic matter, and from dry or wet deposition. Loss of nitrogen occurs via leaching and gaseous emissions.

The resulting biomass production is partitioned between roots and shoots, whereby the initially low shoot allocation increases during plant growth. In principle there are only two biomass compartments in the crop module, and only at harvest a certain fraction of the shoot, determined by the “harvest index”, is removed as grain. This harvest index is a crop- and variety-specific parameter that can be reduced by water stress, expressed as the ratio between actual and potential transpiration during the last month before harvest. For the calculation of actual and potential transpiration refer to e.g. Parton [1978] and the Century Manual [2005]. The harvest date is scheduled when a crop-specific temperature sum is reached, following the growing degree days concept [Wang, 1960].

The described mechanisms bring about especially sensitive parameters and important implications for simulated yields, which are described in the following section.

Water limitation

As described above, water limitation in DayCent incrementally reduces potential production (at each time step) and harvest index (before harvesting) by relating PET to available soil water and potential to actual transpiration, respectively. PET and transpiration are crop-independent, and transpiration is not included explicitly in water limitation of weekly production but has a direct impact on the available soil water in the next time step. This approach does not allow for a consideration of crop-specific differences in water-use efficiency (e.g. for C4 plants). Instead, plant-specific behaviour is reflected in different sensitivities to drought conditions (parameters T1 and T2 in Figure 3.1a).

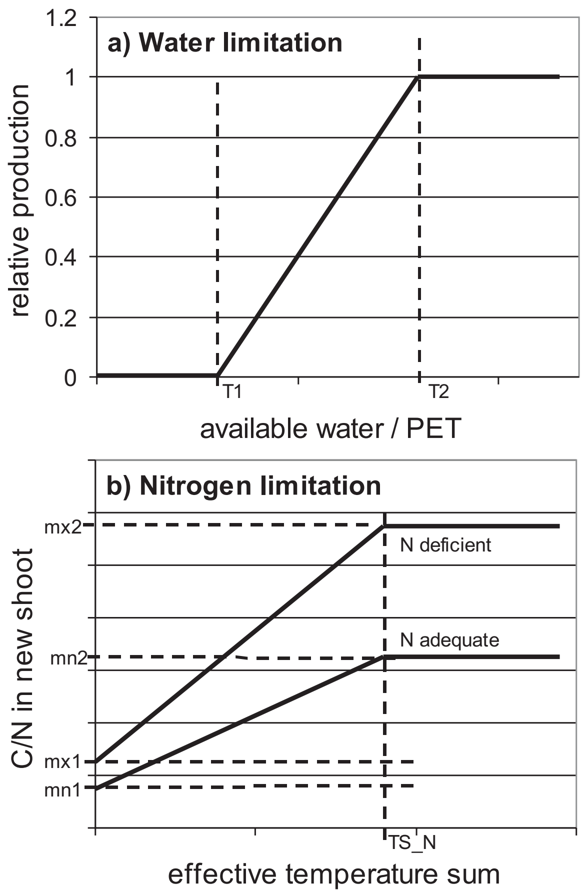

Figure 3.1: Schematic representation of the of water (a) and nitrogen (b) limitation during the growth cycle in the Daycent model. Abbreviations used: C (carbon); N (nitrogen); PET (potential evapotranspiration. Parameters names used: T1 (ratio of available water to PET below which no production is possible); T2 (ratio of available water to PET above which production is not limited by water stress); TS_N (temperature sum at which highest minimum and maximum C/N ratios are reached); mn1 (lower limit of C/N ratio at zero biomass); mx1 (upper limit of C/N ratio at zero biomass); mn2 (upper limit of C/N ratio for effective temperature sum > TS_N); mn2 (upper limit of C/N ratio for effective temperature sum > TS_N).

Temperature

Temperature influences incremental biomass production at each time-step and, via accumulation of growing degree-days, the total duration of plant growth. This causes a complicated overall effect on final crop yield as higher temperatures often increase daily production, but leave less time for the plant to grow. Therefore the optimum temperature for total yield is lower than the optimum temperature for daily biomass production, assuming constant temperature over the entire growth period. Figure 3.2 illustrates this for maize. Temperatures close to T_{base} would result in theoretically infinite duration of the growth cycle and thus in highest grain production. Within the range of realistic growth periods, the crop yield can show a local maximum (e.g. maize), a plateau (e.g. rice) or a steady decrease (e.g. wheat), depending on the crop specific parameters. It is unclear whether this effect can be found in reality or not, and to what extent local crop varieties might compensate for it by higher temperature sum requirements. Nevertheless, it is commonly accepted that at least the shortening of grain-fill duration by high temperatures has significant impact on grain yield formation [Acevedo et al., 2002; White and Reynolds, 2001; Wilhelm et al., 1999].

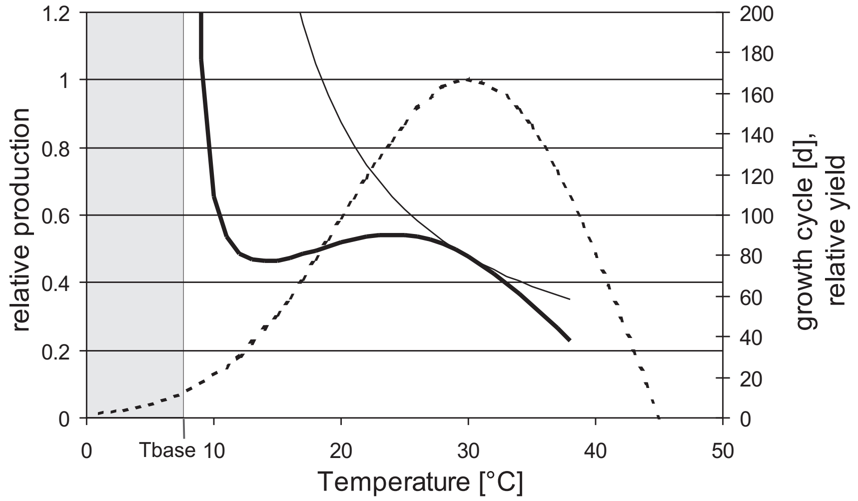

Figure 3.2: Daily production (dashed line), the duration of crop growth until the temperature sum for maturity is reached (thin line) and the resulting relative grain yield (thick line) as functions of temperature (parameterisation refers to maize). Temperature is assumed to be constant over the entire growth cycle.

Nitrogen

As described above, plant growth essentially needs minimum amounts of nitrogen per unit of assimilated carbon (see Figure 3.1b) and therefore available nitrogen sets an upper limit to biomass production at each time step. In agricultural systems the fertilizer input largely governs the availability of nitrogen and thus constrains maximum production. At near steady-state conditions, the yield levels and the associated nitrogen removal with grain will not significantly exceed the annual nitrogen added to the soil in terms of mineral fertiliser, manure, plant residues and depositions from the atmosphere (except for legumes). In fact, yields may be lower because of nitrogen losses via leaching and gaseous emissions.

3.2.2 Planting Dates

As crop yields are sensitive to planting dates and the length of the growing season planting data for different regions of the world are an important input parameter that determines regional crop response to climate conditions. Although some organizations or projects provide information on crop-specific planting dates [FAO-Geoweb, 2004; USDA, 2004] this information is not sufficient for a global yield modelling exercise because of several reasons. First, not all countries and not all crops are covered by these databases. Second, planting dates often differ within one country which is only considered for very large countries in these databases. Third, planting dates change with climate change [Kucharik, 2003; Myneni et al., 1997], and any project that aims to simulate future crop yields can not rely on static crop calendars.

Therefore we developed a scheme to calculate global planting dates on a global 30 arc minutes grid, based on average monthly climate (Climate Research Unit, monthly average for temperature and precipitation for 1961-1990; [New et al., 2000]). For all grid cells within a crop-specific thermal envelope a more detailed consideration of potential growth and water limitation is implemented. For crops that can either be grown as winter or summer crops (e.g. wheat) we assume that the (higher yielding) winter variety is grown wherever the temperature is not falling below a critical temperature during winter (-10°C), but drops below the vernalisation temperature (6°C). These values are adjusted to account for the use of monthly mean temperatures. Planting dates for winter crops are then calculated so that a certain effective temperature sum, which is needed for germination and establishment of seedlings, is reached before the coldest month. For all summer crops the planting date algorithm uses a simplified yield modelling routine to calculate crop yields for all 12 potential planting months, and the planting month with the highest crop yield is then selected as the "optimal" planting month.

The "simplified yield modelling routine" includes a monthly production function and a reduction of potential production by water stress expressed as available water to PET, both analogous to the DayCent algorithms. Accordingly, crop growth continues until the temperature sum for harvest is reached. No yield is formed if temperature drops below a critical value during the growth cycle (like in DayCent), and if the duration of crop growth exceeds or under-runs a crop-specific minimum or maximum threshold. Based on the thus calculated yields of all possible planting months the optimum planting date is selected. Sequential cropping is not implemented in this first version though the algorithms are suitable to optimise double or triple cropping as well.

3.2.3 Input data and simulation methodology

All data sets used for the global simulation, its spatial resolution and the reference time period are listed in Table 3.1, while a comprehensive description of these data and the simulation methodology is provided in chapter 3.5.

Table 3.1: Data sets used and simulation settings

Data set	Spatial reference	Temporal reference	Source
Weather data	0.5° lat x 0.5° lon	monthly averages 1961-1990	New et al. [2000]
Soil data – Bulk density, C, N	5 arc min x 5 arc min		Global_Soil_Data_ Task_Group [2000]
Soil data – pH, texture	5 arc min x 5 arc min		FAO [1995]
Land use	Crop fraction on 5 arc min grid	early 1990ies	Leff et al. [2004]
Management – fertilizer nitrogen application	Country averages	mid 1990ies	IFA [2002]
Management – manure nitrogen application	Country averages	mid 1990ies	Siebert [2005]
Planting dates	0.5° lat x 0.5° lon	Based on climate 1961-1990	this study
Fertilizer application dates	depending on planting & harvesting dates; 0.5° lat x 0.5° lon, application in four events		
Manure application dates	depending on planting &harvesting dates; 0.5° lat x 0.5° lon,, application in two events		
Irrigated area	Irrigated fraction on 5 arc min grid	mid 1990ies	Siebert et al. [2002]
Global simulation	0.5° lat x 0.5° lon, using dominant soil type of 5 arc min soil map	30 years, last 10 year averages as results	

3.3 Results and Discussion

3.3.1 Global planting dates

The planting dates for wheat, rice, maize and soybean calculated as described in section 3.2.2 are shown in Figure 3.3a-d. The only possible way of validating these results is by comparing them to crop calendars [FAO-Geoweb, 2004; USDA, 2004] which are in most cases not spatially explicit, but provided as country-specific values. Therefore simulated planting dates were averaged over the entire crop-specific area within one country [Leff et al., 2004] and then compared to the crop calendar (Figure 3.5a-d). This approach will certainly cause problems in countries where planting dates and crop distributions are not homogenous within the crop area. In addition to the actual planting date the planting routine indicates whether a crop can be grown at all under the temperature regime of a certain location (see 3.2.2). In Figure 3.3a-d this temperature envelope is marked in grey.

Wheat

Planting dates for wheat are primarily determined by criteria allowing winter or only summer wheat cropping. The expansion of winter wheat to high latitudes, which is determined by the minimum winter temperature, is met reasonably well as shown in Figure 3.4 for China and the US. The growing of winter wheat towards lower latitudes is restricted by low temperatures needed for vernalisation. But even in regions where temperature does not fall below the vernalisation threshold the simulated optimal planting date for summer wheat is before the coldest month, i.e. around December for the Northern Hemisphere, e.g. in Spain and the southern USA, (Figure 3.3a), which is also reported by USDA data [USDA, 2004].

In addition to the summer-winter wheat pattern it can be observed that planting of winter wheat is simulated later in the year towards lower latitudes. The crop calendars from USDA for European countries report planting dates from Sep-Oct in Sweden to Nov-Dec in Spain [USDA, 2004], and the simulated planting dates agree very well with this trend (Figure 3.3a). The explanation for this effect is that in the North the development to the phenological state essential before the onset of winter is slower and, additionally, winter begins earlier.

Figure 3.5a shows the country-level comparison between simulated planting dates and crop calendars. For countries where both winter and summer wheat are grown the two varieties are represented by separate data points (Canada, Russian Federation). A significant clustering of planting dates can be observed around Sept-Dec (northern-hemisphere winter wheat and southern Hemisphere spring wheat) and May-September (northern-hemisphere spring wheat and southern Hemisphere winter wheat) with winter wheat countries accounting for the majority of the data points represented.

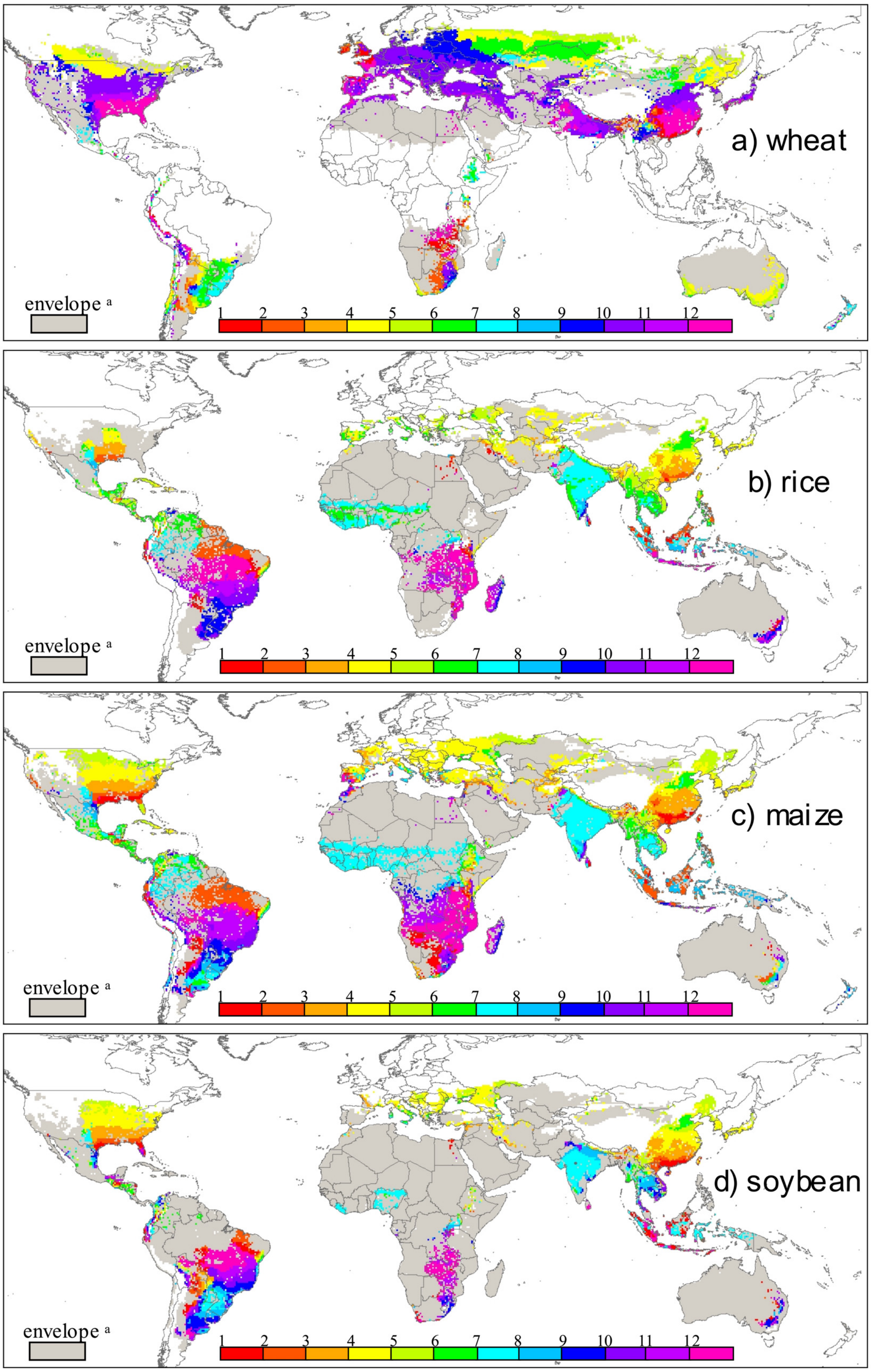

Figure 3.3: Global planting dates for wheat (a), rice (b), maize (c) and soybean (d), masked with the crop area according to Leff et al. [2004].
[a] The complete envelope comprises the coloured planting date areas plus the grey area.

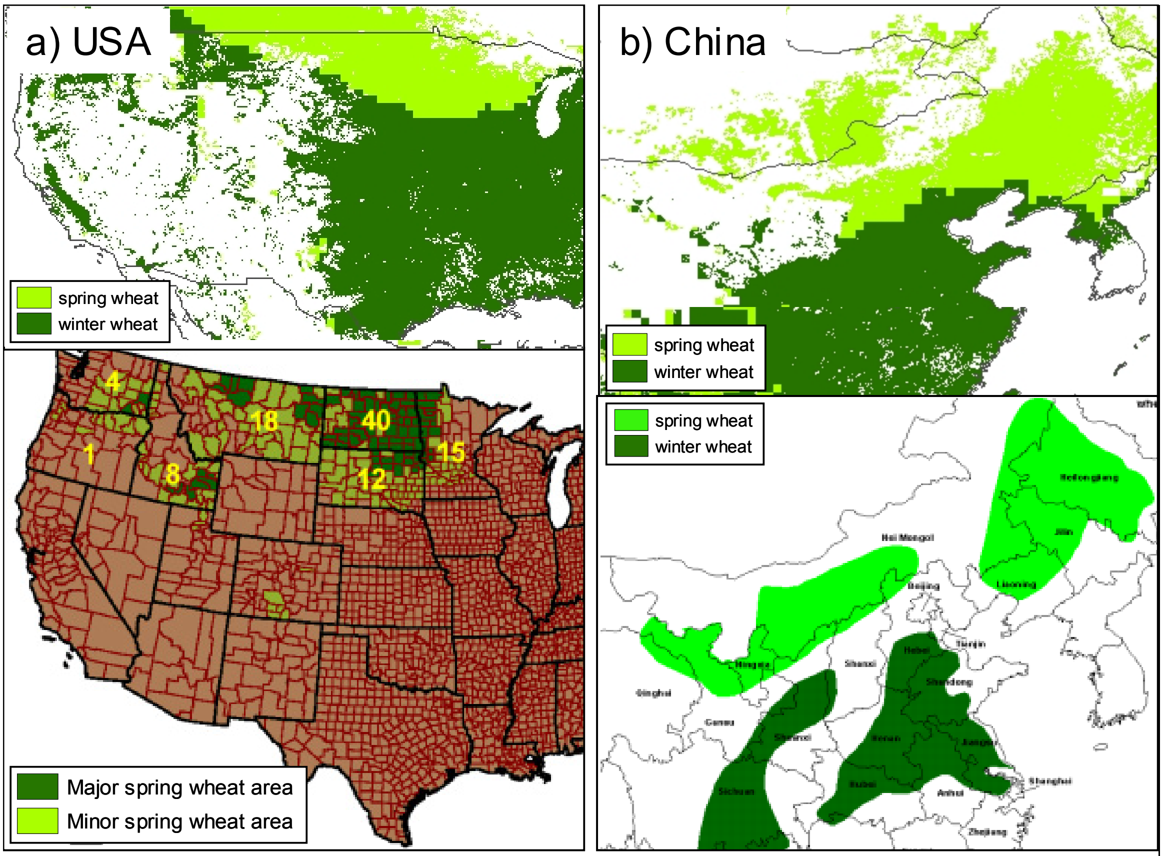

Figure 3.4: Areas of winter and summer wheat cropping in the USA (a) and China (b) (acc. to USDA), and simulated boundary between summer and winter wheat.

Figure 3.5a generally indicates that simulated planting dates for wheat agree reasonably well with crop calendars, only South Africa and Zimbabwe are far off. This is due to the planting routine selecting the optimum planting date under *rain-fed* conditions. In countries where almost 100% of the respective crop is irrigated like in Zimbabwe and South Africa, this may differ from the actual (irrigated) planting date, and when calculating the irrigated planting date it agrees with the crop calendar. This trade-off between temperature and water limitation is also present in the rest of southern Africa, where the planting routine predicts October to December for wheat (therefore summer wheat) to take full advantage of the rainy season, while the crop calendars' planting dates are around June (therefore winter wheat), to benefit from the lower and thus more suitable winter temperature, even though there is no significant irrigation (data not shown). It therefore has to be concluded that the planting date routine overemphasizes the water over the temperature regime, which causes false estimations in some arid countries.

Another miscalculation of planting dates occurs in the high latitudes, where snow-melting can provide a considerable amount of water in summer-dry areas, and where crops are therefore planted soon after. The planting date routine does not include a snow module so far, and therefore calculates later planting dates. This phenomenon only affects the coldest margins of cropping areas with additional occurrence of pronounced droughts during spring and summer. It is relatively uncommon and not significant for most countries. But for Kazakhstan the systematic underestimation (Figure 3.5a and 3.5c) can partly be explained by the ignorance of melting water.

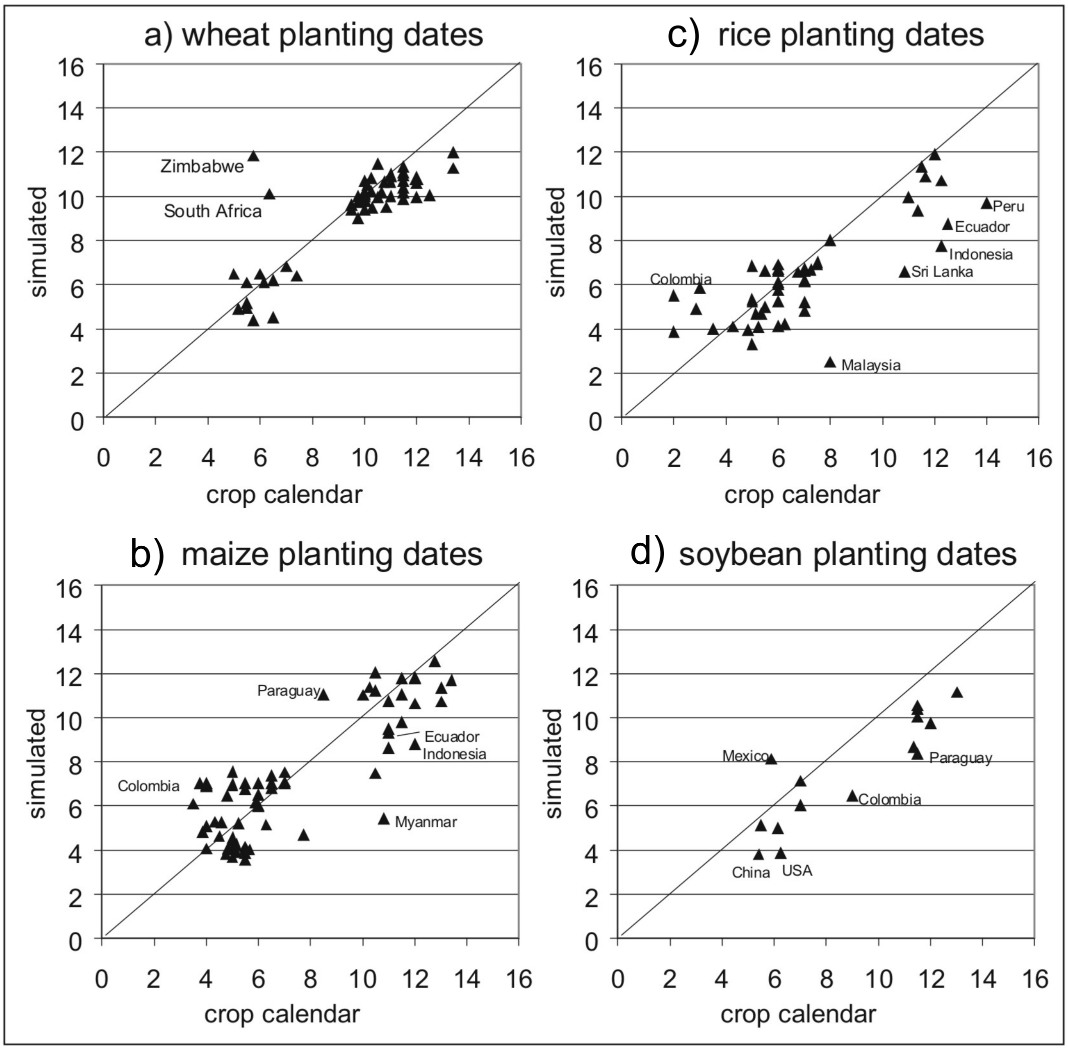

Figure 3.5: Comparison of simulated planting dates and FAO crop calendars [FAO-Geoweb, 2004] per country for wheat (a), rice (b), maize (c) and soybean (d).

Rice, maize and soybean

Planting dates for rice, maize and soybean (Figure 3.3b-d) show similar patterns and problems and will therefore be discussed together. Their agreement with crop calendars is reasonably good though some significant discrepancies occur in all plots. These can partly be explained in the following way:

Many islands or insular states exhibit complex precipitation patterns, often completely differing on opposite sites of an island, which make it impossible to estimate a single planting date. Therefore simulated planting dates differ significantly from crop calendars for some Southeast-Asian countries like Indonesia (rice and maize), and Malaysia and Sri Lanka (rice).

A similar problem occurs in countries with strong climatic and elevation gradients like in the north-western Andes states of Latin America, causing almost chaotic planting date patterns in Colombia, Ecuador and Peru. Averaging over these data leads to almost random agreement or disagreement with crop calendars for these three countries.

Another inaccuracy is caused by the discrepancy between real crop area and the area over which the average is calculated. The global map of crop distribution [Leff et al., 2004] only includes sub-national data for Canada, the USA, Mexico, Brazil, Argentina, Turkey, the Russian Federation, China, India and Australia, but for all other countries the crop area is almost identical to the agricultural area and therefore often differs from the "real" crop area as e.g. reported in FAO-GeoWeb [2004], which was not available in a geo-referenced electronic format. This leads to inaccuracies in the averages, especially if planting dates show strong gradients within a country. The only way of addressing this problem is by including sub-national data and/or the maps provided by FAO-GeoWeb [2004] to improve the crop distribution map.

The fourth problem occurs if there is a wide range of planting dates within a country's crop area. In some cases FAO provides the complete range of planting dates, and therefore FAO average and simulated average may agree, but sometimes only the crop calendar for the main region or even two crop calendars (for several African countries) are given. For the US and China, the USDA [2004] provides information that rather applies to the northern area, while stating that planting dates are 1-2 month ahead in the southern part. As we consequently applied the crop calendar as it is and did not manipulate it based on such statements, simulated average planting dates of rice, maize and soybean are ahead of time for these countries (Figures 3.5b-d). Another example for this phenomenon are some central African countries like Congo, where a steep north-south gradient of planting dates is observed and therefore two crop calendars are provided. The same shift is present in the simulated planting dates, proving that the essential mechanisms are very well captured. In these cases (Congo, Uganda) only one crop calendar and the simulated average over the respective area are compared.

3.3.2 Thermal Envelopes

The (thermal) envelope allowing the production of a specific crop calculated by the planting date routine is presented in Figures 3.3a-d, by the coloured presentation of the actual planting date (on the actual crop area) and in grey (outside the actual crop area). A grey envelope area extending to higher latitudes than the crop area indicates a "larger" envelope than actually used for crop growth. No additional grey envelope area towards the poles indicates an agreement between the envelope and the crop distribution or a too restrictive envelope, though this conclusion is only valid if the crop distribution map includes sub-national data that are detailed enough to reflect small scale crop distribution. In the southern hemisphere the envelope of all crops is expanding further south than the crop area, while in the northern Hemisphere northern borders of envelope and crop area almost match. The only exceptions are the Russian Federation, where the area of all crops seems to expand further north than the respective envelope because of too coarse sub-national data, and China, where the envelope is too restrictive for rice. That also agrees with a comparison to the crop distributions provided by FAO-GeoWeb [2004] or USDA [USDA, 2004], which were both not available electronically.

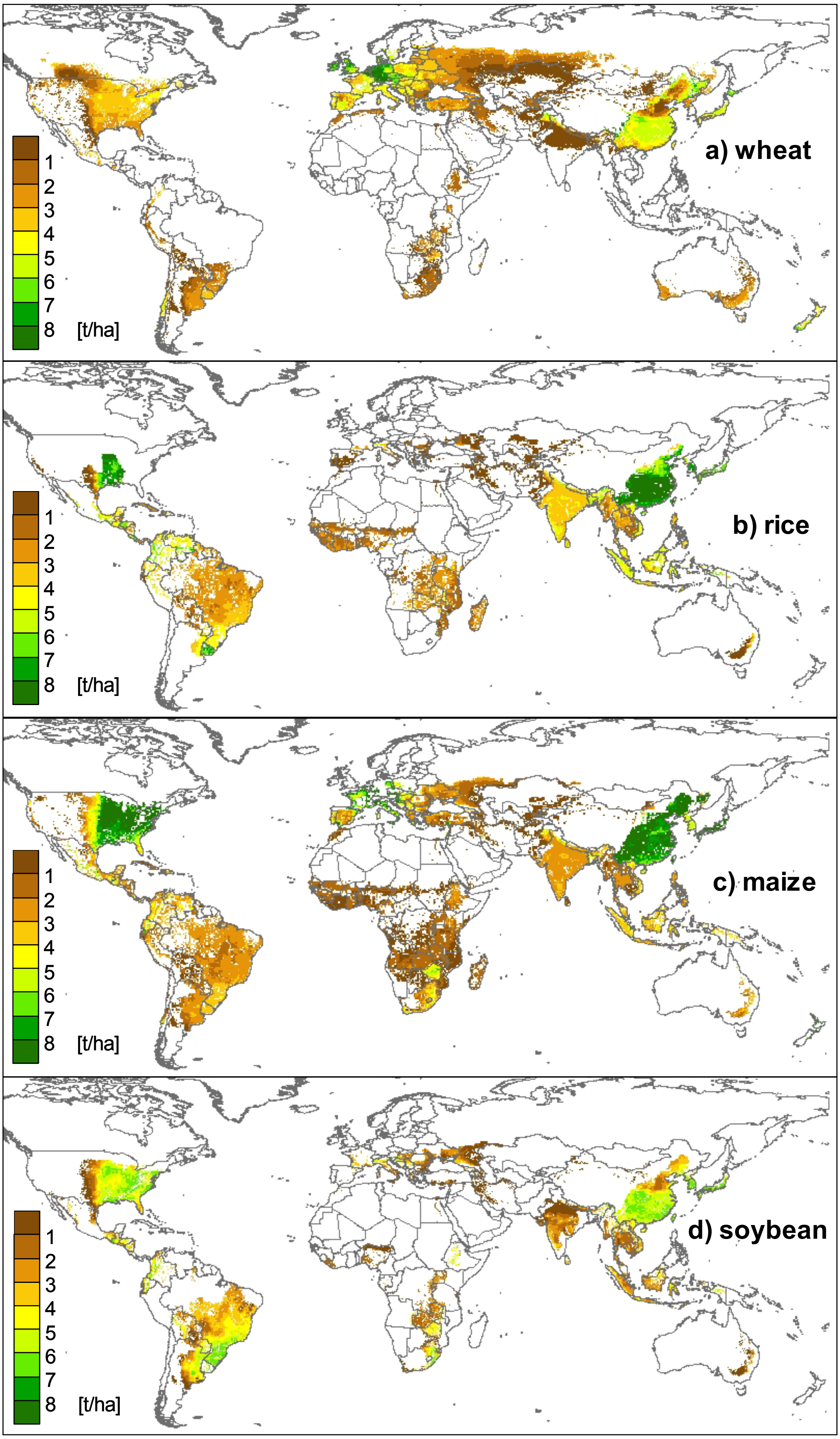

Figure 3.6: Global yield levels for rain-fed wheat, rice, maize and soybeans as simulated by Daycent.

3.3.3 Global crop yields

Based on the planting dates and the input datasets listed above DayCent simulations were carried out. Yields were averaged over the last ten years of the 30-year simulation period and are presented as maps in Figures 3.6a-d.

Several strategies can be employed to test the performance of a global crop production model. The use of experimental site data is desirable in that such data usually comprise detailed information about weather, soil, management and yields. However, it was beyond the scope of this study to compile site data from all around the world in order to represent the various climate, soil and management conditions. The second way is to compare the simulated yields against census data, which is available on the sub-national to national scale. Since the DayCent model will be integrated into a global land use change model, it is important that it captures the differences in national yield levels. We thus decided to test our simulation results against FAOSTAT data [FAO, 2004] which is provided for all countries of the world. Furthermore, we used sub-national county level census for selected countries in order to test whether DayCent is able to capture the spatial variability of yields (section 3.3.5).

In order to determine national averages of simulated yields we first calculated average rain-fed and average irrigated yield by (1) assigning the simulation result of a 30 min cell to all underlying 5min cells and (2) calculating the weighted average over all crop cells of the 5min land use map. We then weighted rain-fed and irrigated yields according to the fraction of irrigated area per crop which we derived by relating crop-specific irrigated area for the late 1990s as provided from FAO AQUASTAT [2006] to total crop-specific area (FAOSTAT, averaged over the years 1998-2000). If no AQUASTAT data were available for a certain crop or country, the national mean fraction of irrigated area was used for non-rice crops, while for rice we then applied the global average fraction of irrigated rice (64%) as derived from AQUASTAT.

The comparison between the simulated national averages and the national reported yield levels (FAO, average over the years 1991-2000) is shown in Figure 3.7a-d. We chose the FAO 1991-2000 average yield levels because the management data with respect to irrigation and particularly fertilisation is representative of the mid 1990s. The analysis was carried out for all countries with an average agricultural area exceeding 1200 ha (in the years 1991-2000). The single scatter plots only show countries that possess both a reported FAO yield and a simulated yield. To highlight the relevance of a country's crop production we created "bubble plots", with the area of each bubble proportional to a crop's harvested area within that country. These plots are shown in Figure 3.8a-d.

Three different measures of agreement are presented in Table 3.2. The R^2, the R^2 weighted for a crop's area and the R^2 weighted for a crop's total production within one country in order to reflect the relative importance for the global crop market.

	R^2	R^2 weighted for area	R^2 weighted for production
wheat	0.663	0.659	0.652
rice	0.657	0.785	0.795
maize	0.672	0.659	0.522
soybean	0.321	0.558	0.418

Table 3.2: Coefficients of determination for country averages of wheat, rice, maize and soybean yields as presented in figure 3.8.

For wheat all three measures of R^2 are very similar, while for rice large producer countries are better estimated than others, which causes a higher weighted R^2. For maize, weighting by area does not affect the R^2 much, but weighting by production results in a lower R^2, as some countries (especially China) with high yield levels show a considerable deviation from the reported FAO yield. For soybean, the effect of weighting is strongest, as simulation results for the few countries dominating global production are – except for China – much closer to reported yield than on average.

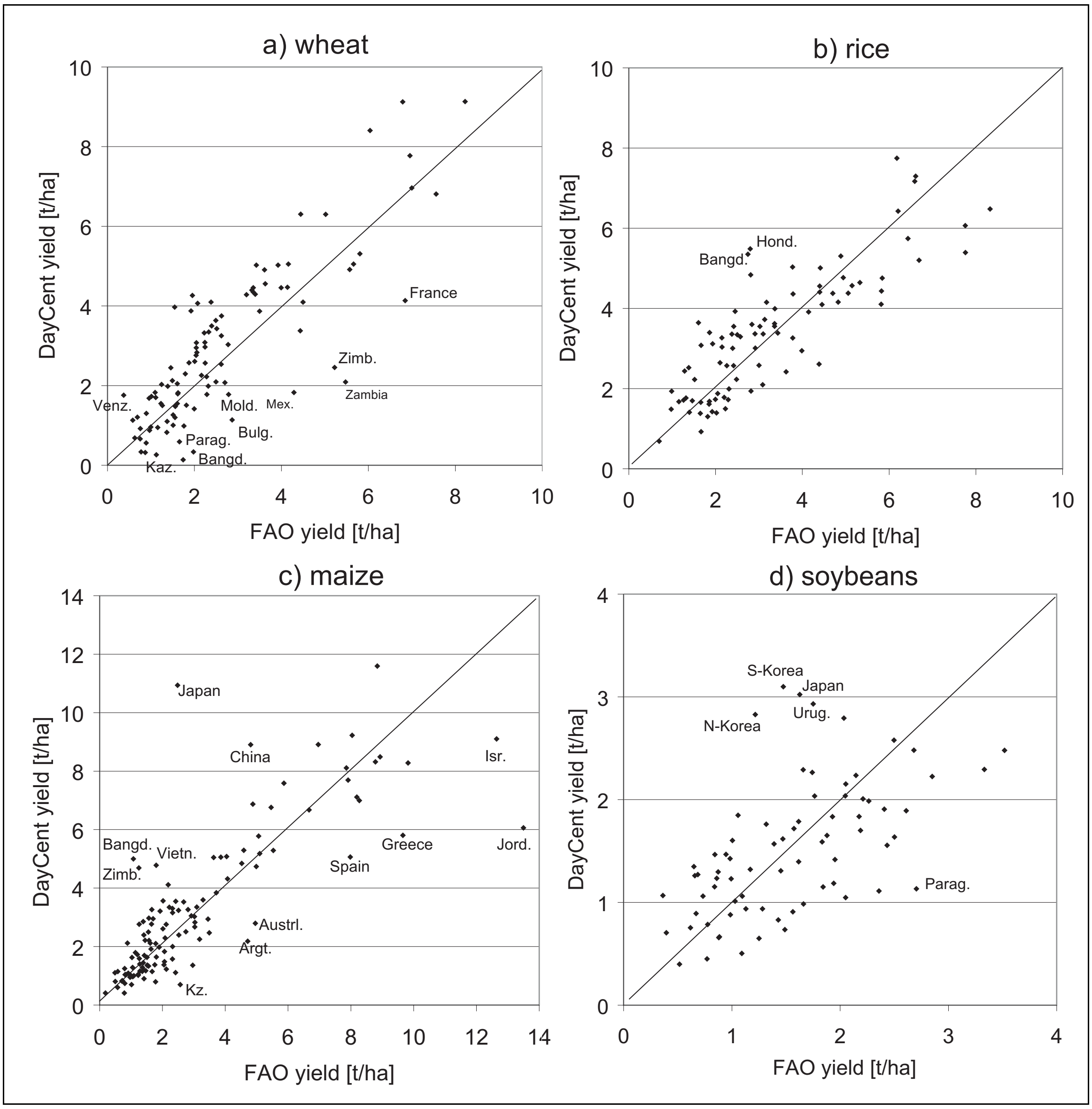

Figure 3.7: Comparison of simulated yields and FAOSTAT data per country for wheat (a), rice (b), maize (c) and soybean (d).

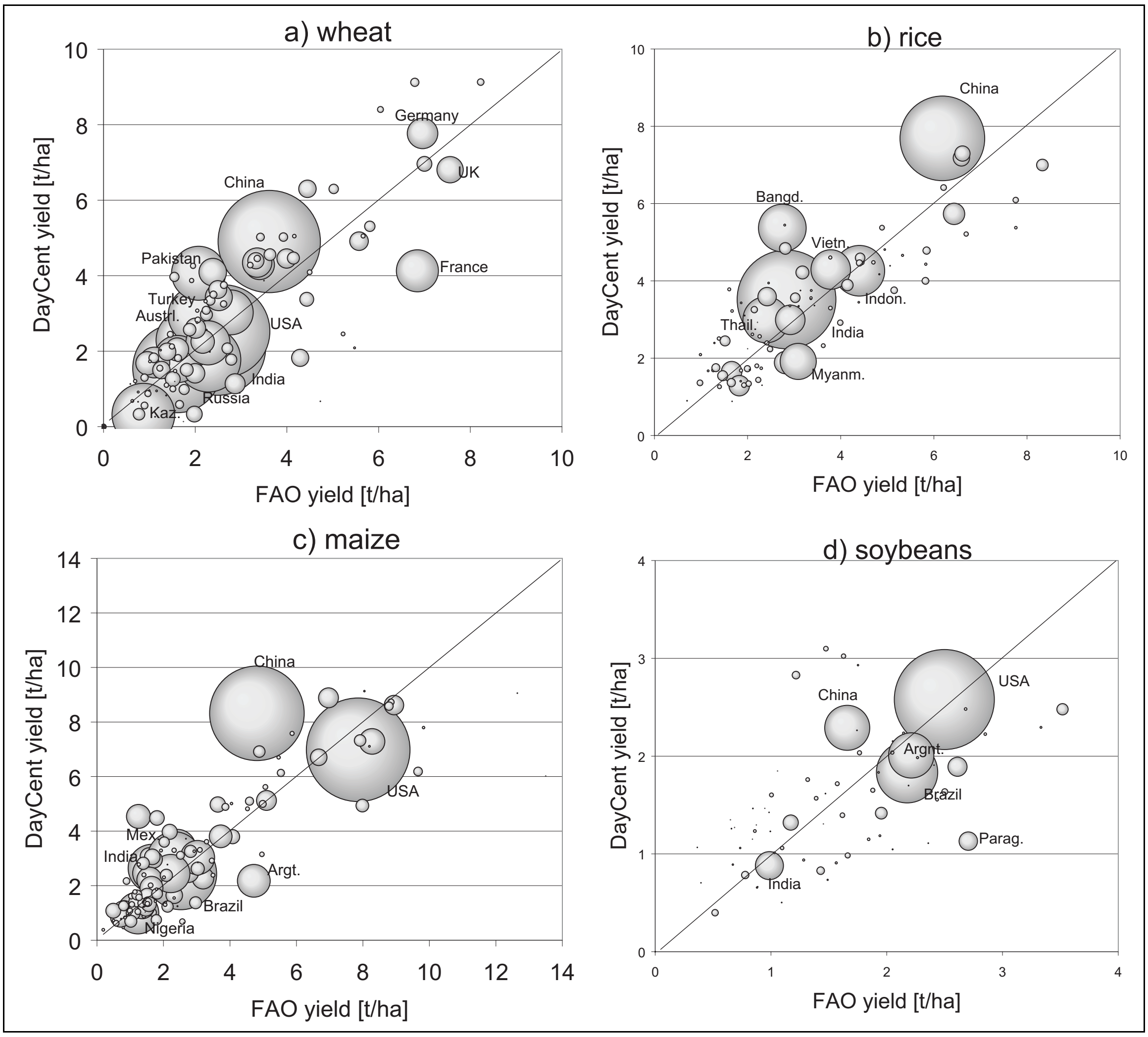

Figure 3.8: Comparison of simulated yields and FAOSTAT data per country for wheat (a), rice (b), maize(c), soybean(d). Areas of circles represent crop area.

In total, the level of agreement for wheat, rice and maize (unweighted $R^2 \approx 0.66$) seems acceptable considering the uncertainties inherent to data and computation of crop yields. A comparison to the modelling efficiencies of other global crop models is not possible at the moment, as only one other global crop model has been applied to represent FAO yield data – the EPIC model –, but no measures of agreement or deviation are reported [Tan and Shibasaki, 2003]. Other large-scale crop modelling studies report R^2 values of e.g. 0.46 [Kucharik, 2003] and 0.0–0.74 [Challinor et al., 2004]. Beyond, we have shown that - except for China - the model captures the yield levels of the major crop producers correctly. On the other hand, we found that the lack of nitrogen limitation for soybeans has severe implications for the level of agreement between simulated and reported yields, and that the provisional approach to account for phosphate limitation (as described in the appendix) improves accordance with FAO data, but still leaves much of the variability unexplained.

3.3.4 Uncertainties

The uncertainty in a number of input data sets was identified to strongly affect simulation results. In the following, we discuss the most important effects.

Fertilizer application rates

One of the most sensitive parameters for DayCent crop growth is the availability of nitrogen, mainly determined by inputs of mineral fertilizer or manure. In the long run, FAO yield levels can only be reached if the total nitrogen input approximately equals the nitrogen removal associated with this yield level, whereby nutrient mining can compensate for insufficient nitrogen supply to some extent. Large discrepancies between nitrogen application rates from the international fertilizer association (IFA) and the amount of nitrogen that would be removed with the reported FAO yields cause a significant underestimation of crop yields for several countries: France, Bulgaria, Moldova Republic, Lithuania, Bolivia (wheat) and Argentina, Bolivia and Moldova Republic (maize).

On the other hand there are several countries where the input of mineral fertilizer reported by IFA largely exceeds the nitrogen that would be removed with FAO yield levels. In some of these cases, when a country's climate is favourable for the respective crop or if the fraction of irrigated area is high, the high nitrogen input causes an overestimation of crop yields. This can be seen for Honduras, Pakistan and Venezuela (wheat), for Bangladesh and Honduras (rice), and for Bangladesh, Guatemala, Japan, Viet Nam and Zimbabwe (maize). As an example we show for maize the total annual nitrogen input through manure and mineral fertilizer versus the annual nitrogen removal that would be associated with FAO yield levels (figure 3.9).

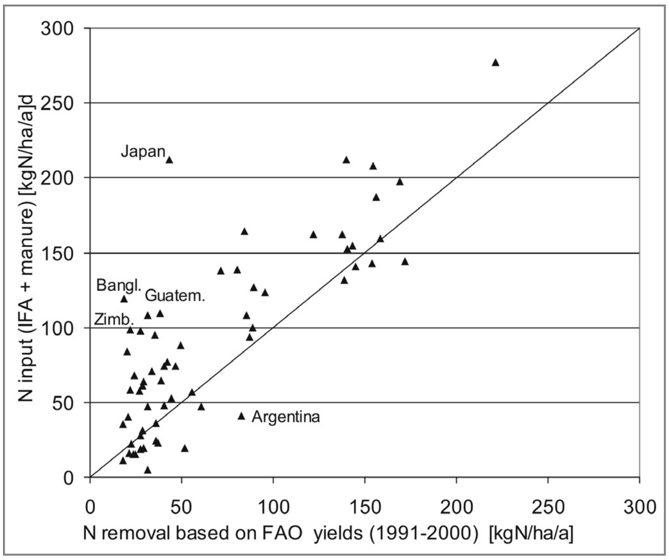

Figure 3.9: Comparison of total nitrogen input (mineral fertilizer + manure) and N removal through harvest according to FAO (yield * N content) for maize.

Irrigated area

In large areas of the world irrigation significantly increases agricultural production. Many countries have significant fractions of irrigated cropland. Therefore data on the actual fraction of irrigated area *by crop* is crucial to correctly estimate a country's average crop yield. Crops like maize and soybean have particularly high water demands [Allen et al., 1998] and are thus known to be irrigated above-average [Iglesias and Minguez, 1997; Kapetanaki and Rosenzweig, 1997]. If no crop specific irrigation data are available, the yields of these crops tend to be underestimated. This can be seen for maize yields in Spain, Greece, Australia, Israel and Jordan, and for soybean yields in Syria, Spain, Greece and Australia. Accordingly, crops which are commonly irrigated below average tend to be overestimated as can be seen e.g. for wheat in Spain, Greece and Israel.

Crop specific area

As described above, national yield levels were derived by averaging the simulated yields over the entire crop area of the land use map, weighted by crop fraction. This will lead to false estimates in countries where the real crop area differs from the land use map similarly as it has already been discussed for the averaging of planting dates (section 3.3.1). Leff et al. [2004] consider sub-national data for Argentina, Australia, Brazil, Canada, China, India, Kazakhstan, Mexico, the Russian Federation, Turkey and the US. In all other countries, they distributed the specific crop area homogeneously over the entire agricultural area. Furthermore, for some countries the spatial resolution of the sub-national census is very coarse and covers very different climatic conditions (e.g. Australia and the Russian Federation). The problem of heterogeneous crop distribution can only be solved by including more detailed sub-national statistics which was done in our study only for soybeans in Australia and Italy [ABS, 2000; Eurostat, 2004]. For most other countries, additional sub-national data was either not directly available (not as geo-referenced digital data, e.g. USDA and FAO-GeoWeb) or its consideration would have been beyond the scope of this study. Thus, strong deviations remain. For example in Paraguay, simulated yields and crop area according to USDA are concentrated in the southeast, while the crop areas according to Leff et al. [2004] which were used for averaging are distributed almost over the entire county. This 'mislocation' leads to an underestimation of all crop yields (Figure 3.7) except for rice, which is irrigated by 100% and therefore not affected by this problem.

Planting dates

The planting date is another crucial parameter for simulated crop yields, as it influences the temperature and precipitation regime under which the crop will grow. In general, the planting date routine produces reliable estimates (section 3.3.1). However, the underestimation of crop yields in some arid countries can be attributed to incorrect planting dates. For non-rice crops we use the "rain-fed" planting date, as in most regions rain-fed agriculture is dominating, and in many cases the availability of water for irrigation is assumed to follow the seasonal fluctuation of precipitation. But for arid areas, where rain-fed cropping is virtually impossible and the entire crop area is irrigated, planting dates may be rather adjusted to the temperature regime. But as there is no straightforward concept to decide whether to use irrigated or rain-fed planting dates we decided to keep the rain-fed planting dates and only explain when this leads to potentially incorrect results (3.3.1). Wheat in Zimbabwe, Zambia and Bangladesh is irrigated by almost 100%, and only our irrigated planting dates agree with those provided by the FAO-GeoWeb (3.3.1). Using the rain-fed planting dates leads to a strong underestimation of yields for these countries (Figure 3.7a), while with irrigated planting dates simulated yields almost double.

3.3.5 Selected spatial patterns

National averages of crop yields as presented in the previous section are strongly determined by national fertilizer application rates, therefore a model's accurate sensitivity to spatial parameters like climate and soil can be more rigorously assessed by comparing spatial patterns of crop yields.

In the following, we compare the simulated spatial patterns of wheat yield to sub-national census data from the US [USDA, 2004], averaged over the years 1992-95, and from Australia, averaged over the years 1993-95. We chose these examples, as both countries have significant climatic gradients and because yield data were available at the county level.

Wheat cropping in the US

In Figure 3.10 we present the spatial pattern of wheat yield in the USA. The census also provides the fraction of irrigated wheat for many counties, particularly west of 95°E where most irrigated wheat areas can be found. This information was used to calculate weighted simulated rain-fed and irrigated yield averages on the county level. Finally, we masked the county areas using Leff et al. [2004].

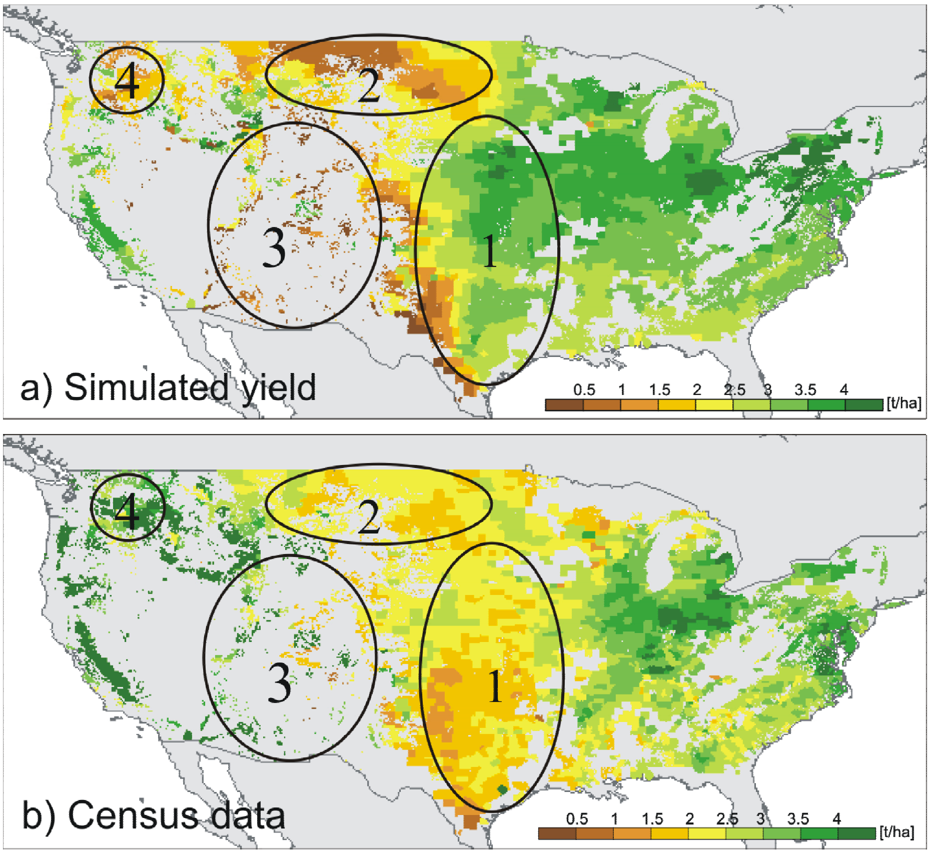

Figure 3.10: County averages of simulated wheat yields (a) and USDA census data (b) for wheat yields in the US. Circles indicate regions that are explicitly discussed in the text.

Yield levels are estimated accurately in the eastern part of the country, ranging from about 4 t ha^{-1} in the northeast to about 3 t ha^{-1} in the south-eastern part. This north-south gradient can be attributed to higher temperatures causing a shorter growing period and partly also lower weekly production. The east-west transition to lower yielding areas in the Great Plains is located too far westwards in the DayCent results compared to the county data (Figure 3.10, circle 1). Beyond, the simulated east-west yield gradient is much too sharp. The second significant discrepancy between simulation results and county data occurs in the Northern Great Plains of the US (Figure 3.10, circle 2). The low simulated yields in circles 3 and 4 show only rain-fed yields as no irrigation data were available for these counties. However, Döll and Siebert [2000] show spots of irrigated areas for these counties which explains the high census yield.

The discrepancies in circles 1 and 2 might be explained by the following:

(i) Imperfect representation of water stress in the DayCent model, (section 3.2.1) may lead to the observed underestimation of the drought effect in the eastern part of the Great Plains, while we overestimate the impact of drought in the western part of the mid-west. Accordingly, we seem to overestimate the impact of water stress in the Northern Great Plains of the US, were water is limiting crop production.

(ii) Spatial variability of fertiliser input might be important, too. For our simulation, we apply only one fertilisation rate for the entire US (80 kg N/ha), although fertiliser application varies spatially [Donner and Kucharik, 2003].

(iii) Impacts of interannual climate variability might cause a discrepancy because of different reference time periods. For our global simulation, we used climate normal data for 1961-90, while the census data is representing average yield only for the years 1992-95.

Wheat cropping in Australia

For Australia the fraction of wheat area according to Leff et al. [2004], the simulated wheat yield and county data of wheat levels are presented in Figure 3.11. Wheat specific irrigation data were not available, and as the average irrigated fraction of agricultural area only amounts to 5%, simulated county averages were calculated only based on the rain-fed yield. To ease and accentuate the interpretation, a black line was drawn along the northern edge of wheat cropping [Leff et al., 2004] and superimposed to all maps.

Except for the eastern and north-eastern regions the transition from high wheat fractions (around 80%) to virtually no wheat cropping is very sharp, indicating that wheat is dominating agricultural area up to its northern margin imposed by a strong climatic gradient. This rather sharp transition from suitable to non-suitable conditions is present both in the simulation results and the county data. South of this line simulated yields and county data show similar gradients with highest yielding areas in the south-west, the south-east and Tasmania. Beyond these common features difference in yield levels can be attributed to the similar mechanisms already described above:

(i) Irrigation of wheat leads to high average yield levels under the arid conditions of some central counties, though the absolute wheat area in these counties is very small (Figure 3.11a).

(ii) An inconsistency of reference periods causes an apparently slight overestimation of wheat yield. While we used 30-year averages of climate, county-specific yield data were only available for the years 1992-1994, which were significantly lower than longer-term averages (in 1994 Australian yields only reached half of the normal level [FAO, 2004]).

(iii) Steep slopes in the south-eastern part of Australia are restricting wheat yields and wheat area (Figure 3.11a), which is not included in the model and therefore leads to the observed overestimation (see 3.3.7).

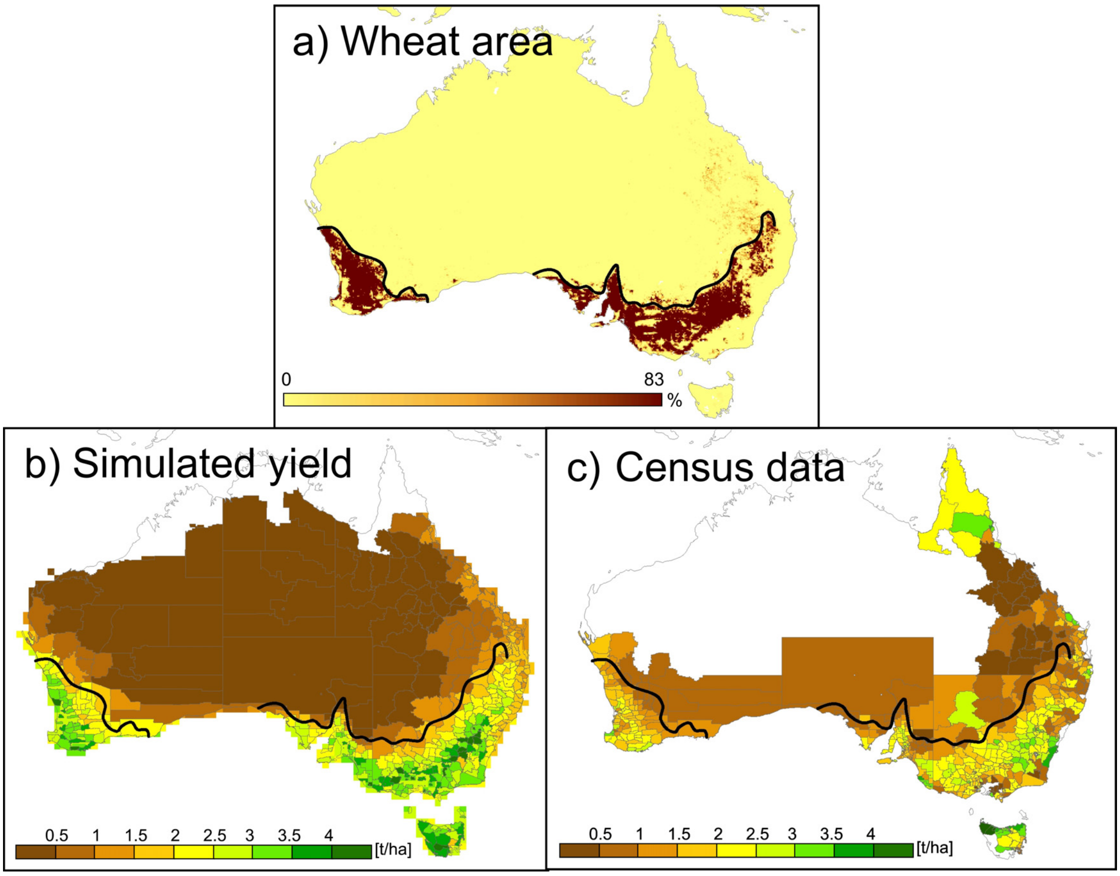

Figure 3.11: Fraction of wheat area (a) and county averages of simulated wheat yields (b) and census data (c) for wheat cropping in Australia.

3.3.6 Simulation of other crops

The four crops presented here cover about 40 % of the global agricultural area. In addition, we also calibrated DayCent for the simulation of sorghum, temperate and tropical pulses, potato, sweet potato, cassava and cotton. The presentation of these additional results does not provide additional insight, as most of the effects discussed here are also relevant for the other crops. However, we provide global yield maps of these crops in appendix A.

3.3.7 Methodological issues

In a strict sense, the comparison of average national simulated crop yields and FAO data is no validation of the DayCent model. After parameterising the model based on literature reviews (e.g. effective temperature sum, base temperature, C/N ratios, harvest index, drought and frost tolerance) average national crop yields were simulated. If necessary, a calibration was carried out by modifying the crop-specific energy-biomass conversion factor “prdx” (identical calibration for all countries). The final results were again compared to these FAO yield data and to selected spatial patterns of yield as derived from sub-national census. Though that is not a validation of the model, it still serves as an evaluation of model performance, as only one parameter was calibrated for datasets containing 74-127 records.

Another critical methodological aspect is the climate data set. Because of mainly technical reasons we used 30-year averages of monthly precipitation and temperature from the years 1961-1990, although management and FAOSTAT data refer to the mid-1990s, and although this approach does not account for inter-annual and daily climate variability. The sensitivity of the model to monthly instead of daily values and to the reference time period was tested by additional simulations with (1) daily climate data on a 2.5° grid [ECMWF, 2004], and (2) with monthly average for the years 1991-2000 [Mitchell et al., 2004]. The results of the first analysis were dominated rather by the effect of the coarser spatial resolution than the finer temporal resolution. Although the ECMWF data set in general provides reliable temperature and precipitation data, the simulated yields are lower (up to 20%) compared to the standard simulation in areas with small-scale gradients of elevation, climate and – as a result – land use like Switzerland because temperatures on a 2.5° grid cell tend to be lower than the actual temperatures over the agricultural area within this grid cell, which often is located only at the lower elevations (data not shown). As for the second analysis, using average climate from 1991-2000 [Mitchell et al., 2004], the global results indicate a low sensitivity to the different reference time periods (good agreement between simulation results for 61-90 and 91-00; bias = 1.02, R^2 = 0.96).

The DayCent model does not account for the impact of slope on crop yields. However, slope impact on crop yield is undisputed, is substantiated by statistical analysis [Jiang and Thelen, 2004; Ping et al., 2004], and can be attributed e.g. to water stress through increased surface runoff, and to erosion reducing soil fertility and decreasing the rootable depth [Strauss and Klaghofer, 2001]. Furthermore sloping land restricts accessibility and the use of machinery, and has strong gradients in micrometeorological parameters. Most national averages are calculated accurately without slope effects because for most countries the agricultural areas are restricted to rather plain lowlands. Nevertheless there are some countries where significant fractions of cultivated land are sloping. This might cause the systematic over-estimation of simulated yields for non-rice crops in e.g. North- and South Korea and Japan.

A consistent implementation of slope effects in DayCent can not rely on simple yield reduction factors like the GAEZ model [Fischer et al., 2002], but would require a process-based approach like in the EPIC model [Williams et al., 1984].

3.4 Conclusions and Outlook

As we have seen, large scale crop modelling is subject to a wide range of uncertainties, with respect to both input data (particularly management), and the representation of processes influencing crop growth (e.g. formulation of water stress, phenological stages, impact of slope, etc.). Despite these uncertainties there is an urgent need for global crop models to assess future large-scale changes in land use, to study the impacts of climatic change on crop yields in different world regions, to examine the environmental consequences of agricultural practises, and to analyse potential feedbacks between the terrestrial and the climate system. Therefore an integrated approach is needed to model plant production, the water cycle and carbon and nitrogen fluxes.

The adaptation and application of the DayCent model presented here provides an appropriate tool to address these issues, as it includes a detailed representation of soil biogeochemistry and is able to reproduce the major effects of climate, soil and management on crop production. We have shown that average simulated crop yields per country agree well with FAOSTAT yield levels ($R^2 \approx 0.66$ for wheat, rice and maize; $R^2 = 0.32$ for soybean) and that spatial patterns of yields mostly correspond to observed crop distributions and sub-national census data.

Beyond, our study demonstrated that further improvement of the DayCent model will be achieved by implementing water stress as the relationship between crop-specific actual and potential transpiration, by including phosphorous limitation for legumes and by accounting for the effect of slope on surface runoff, water and nutrient availability.

To account for the diversity of agricultural management at the global scale it is crucial to include regional differences in crop varieties and sub-national variability of management practices, e.g. based on the Farming Systems Map [Dixon et al., 2001], and to implement sequential cropping and crop rotations, which are relevant for soil nutrient dynamics and realistic planting dates.

Among the different possible validation strategies for global crop models the approach followed here will be substantially improved if more accurate maps of global crop distribution are available to calculate national averages of planting dates and crop yields. Furthermore, remote sensing data (particularly leaf area index estimates) bear potentials e.g. for the identification of planting dates and phenological development, and the effect of water and nutrients on crop yields should be evaluated in more detail, possibly by using site data of crop growth. A first initiative on such a database that should cover the variety of environmental and management conditions around the world was taken recently during a crop-modelling workshop at Rothamsted, UK [Scholze et al., 2005].

With a tool at hand that integrates plant growth, water, carbon and nutrient cycles at the global scale it is now possible to study the effects of climate change and inter-annual climate variability on crop yields in different world regions, and to extend this approach to assess the impact of agricultural management on soil nitrogen dynamics and trace gas fluxes, or to calculate agricultural water demand and the impact of irrigation on crop yields.

3.5 Supplement: input data

3.5.1 Climate data

The DayCent model uses daily data on precipitation and maximum and minimum temperature, but on the global scale the choice of climate datasets is very limited. There are daily data on a 2.5° x 2.5° grid, provided by several research centres like ECMWF or NOAA, either as model results or as reanalysis data [ECMWF, 2004; NOAA-CIRES, 2004]. A finer 0.5° x 0.5° spatial resolution of climate data can be obtained from the Climate Research Unit, East Anglia, but only as monthly averages. For our core modelling we used the monthly averages of temperature and precipitation for the period of 1961-1990 [New et al., 2000], by assuming identical temperatures and precipitation for all days within one month. In order to test the effect of the temporal resolution and the reference period we carried out sensitivity simulations with the daily ECMWF reanalysis data

[ECMWF, 2004] and the monthly averages for the period 1991-2000 [Mitchell et al., 2004]. The results of this analysis are discussed in 3.3.7.

3.5.2 Soil data

A global map of soil properties at five arc minutes resolution can be obtained from the Data and Information System (DIS) framework activity of the International Geosphere–Biosphere Programme (IGBP) [Global_Soil_Data_Task_Group, 2000]. This map contains bulk density, organic carbon and nitrogen content. For texture and pH we used the FAO TERRASTAT database [FAO, 2002], also providing a five arc minutes resolution. Input data like field capacity, wilting point, and hydraulic conductivity were calculated from these basic data by applying the formulas suggested by Saxton et al. [1986]. To save computing time we did not work on the smallest spatial resolution of input datasets (5 arc minutes soil map) but on a 0.5 degree grid, using the dominant soil type from the finer 5 arc minutes grid.

3.5.3 Land-use map

In order to compare national census data to the simulated yields a land-use map was needed to average the yields over agricultural area or, ideally over the area planted with a specific crop. We used the global map on the distribution of major crops by Leff et al. [2004], which provides the fraction of crop-specific area within each five arc minute grid cell.

3.5.4 Crop types and varieties

For the four crops presented here (wheat, rice, maize and soybean), at least two different parameterisations were used to cover the full climatic range under which these crops can be grown. These parameterisations differ in the effective temperature sum needed to reach maturity (ETS_{harv}). Wheat is represented as spring wheat and winter wheat; for rice, maize and soybean we started with a single variety and then added a parameterisation to also include cooler regions where these crops are cultivated.

Additionally we assumed a low-yielding variety for soybean. As a legume, soybean is not significantly limited by nitrogen, but mainly by other elements like phosphorus, which is not included in our simulations so far. The results of a standard simulation revealed that most countries whose soybean yields were overestimated by more than 50 % are also characterized by extraordinary low phosphate application rates below 10 kg/ha (Figure 3.12). We therefore concluded that for these countries overestimation was due to a lack of phosphorus limitation in the model. We thus decided to emulate this limitation by attributing less productive soybean varieties to countries that are overestimated by more than 50 percent *and* have phosphate application below 10 kg/ha. This was implemented by reducing the productive potential of soybean in these countries by 50 percent (relating to the value of prdx). Note that there are also countries with phosphate application rates below 10 kg/ha that are *not* overestimated (Figure 3.12). For these countries the climatically constrained yield is so low that it can also be achieved with low phosphate application.

The planting date routine (3.2.2) was used to calculate the potential distribution of crop varieties based on the temperature sum required for maturity. If both varieties of a crop could be grown, it was assumed that winter wheat or the tropical varieties of rice, maize or soybean are preferred.

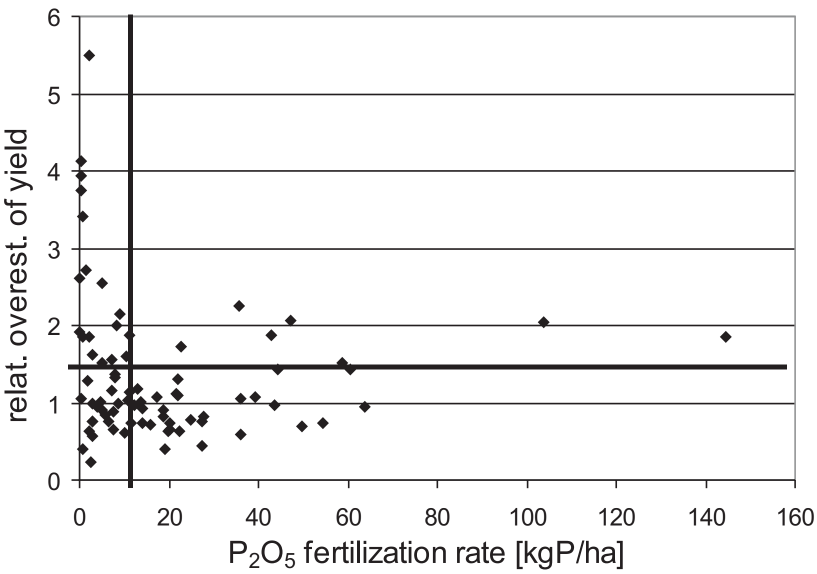

Figure 3.12: Relative overestimation of average soybean yields versus application of Phosphate fertilizer per country according to IFA [2002]. Overestimation = (simulated yield - FAOSTAT data) / FAOSTAT data. Bars indicate overestimation of 50% and a Phosphate application rate of 10kg/ha. For countries with an overestimation > 50% and a P application rate < 10 kg N ha-1 it is assumed that soybean yield is limited by availability of Phosphate (for details see Chapter 3.5).

3.5.5 Initial conditions, simulation period

Matter fluxes between the organic soil pools and the mineralisation of organic matter release mineral nitrogen which directly affects plant growth. The rate at which mineral nitrogen is released by these processes depends on the pool sizes and the related transition rates, following first order dynamics. Thus, the initial conditions for the organic matter pools can be crucial with respect to the simulation of yields. Although the carbon and nitrogen content of the soil is provided by IGBP-DIS, these values may not be in equilibrium under the conditions simulated by DayCent (with respect to climate, land cover and land use). Ideally one would first calculate equilibrium levels of soil organic matter under natural conditions and then retrace a site's development from that state, but as a complete spatially explicit history of global land use could not be constructed in this project, we applied a simpler approach. To avoid the initial effects of changing pool sizes we used a spin-up time of 20 years. Though soil organic matter pools were not always in perfect equilibrium after this rather short period, yields did not change by more than 20 % thereafter.

3.5.6 Management

The term ”management” comprises all activities that are undertaken on a field during the year, like planting, fertilizer application, ploughing, irrigation, and their timing. Though these parameters have an essential influence on crop production, they are often not directly available on the global scale. Therefore the next paragraph describes all management activities and underlying assumptions that were included in the DayCent simulations except for planting dates which have been described in 3.2.2.

Management – Fertilizer application

Only nitrogen was considered as a nutrient in DayCent and therefore fertiliser application only includes mineral nitrogen. We are aware that this is a simplification as according to the Law of the Minimum, any nutrient might cause growth limitation. However, nitrogen is the most important nutrient, and we assume that if farmers apply nitrogen fertiliser at a certain rate, they will apply other nutrients accordingly. This assumption is confirmed by the FAO statistics of fertilizer consumption on country level, where e.g. nitrogen and phosphate consumption show a strong correlation (correlation coefficient of 0.987 for the year 1995). However, as already discussed above, this approach does not hold for legumes since nitrogen is sufficiently provided by fixation.

The amount of nitrogen fertilizer applied per country and crop was derived from the international fertilizer industry association [IFA, 2002], which provides this information for important crop-producing countries and their main crops. The database contains the crop-specific fertilizer application rate and the fraction of area fertilized, which were multiplied to get average application rates. For country-crop combinations with no IFA data available (approximately 17% in cropland area) we calculated the amount of nitrogen that would be removed with yield levels according to FAO statistics as a proxy for nitrogen input and therefore assumed that the difference between the removed nitrogen and the reported manure application rate is applied as mineral fertilizer. To account for nitrogen losses we increased these values uniformly by 10%. However, fertilizer efficiency is often as low as 50% [Cassman et al., 2002; Frink et al., 1999][0] because of leaching and gaseous emissions. As a consequence, the simulations might show nutrient mining or underestimated yield levels for these countries. In addition to the total amount of applied fertiliser, the model is sensitive to the type of mineral nitrogen (nitrate or ammonia). This is due to the processes of denitrification, nitrification and the fact that mainly nitrate is susceptible to leaching losses. We quantified the typical ratio between ammonia and nitrate as a global variable, derived from USGS [2003], resulting into 85 percent ammonia and 15 percent nitrate.

Management – Organic manure application

Nitrogen application from manure was derived from Siebert [2005]. Based on global livestock densities [Gerber, 2004] for 12 animal types and their specific nitrogen excretion, he calculated total nitrogen excretion per grid cell, applying a grid resolution of 5 arc minutes. However, we decided to aggregate the nitrogen application via manure to the country level. This was done (i) to avoid artificial spatial yield patterns caused by nitrogen availability from manure and (ii) to be consistent with the application of mineral fertilizer which is also available on country level. For aggregation, we averaged manure application rates over the entire agricultural area of a country and reduced the overall value by 20 percent in order to account for application losses [Bouwman et al., 1997; ECETOC, 2004; FAO, 2001].

Management – Fertilizer and Manure application Dates

Application dates of mineral fertilizer and manure are difficult to estimate at the global scale. As they are mainly linked to planting dates and crop growth, we applied the following rules to define the application events: Manure is always applied in two identical applications 10 and 30 days after planting. Mineral fertilizer is equally distributed over four application events, taking place 45, 76, 107 and 138 days before the assumed harvest date. If the effective crop growth period is shorter than 140 days the fertilizer is applied in four equal intervals over this period, starting with the planting date. We are aware that fertilizer application in four events does not reflect agricultural practice, but this approach was necessary to achieve realistic fertilizer efficiencies. E.g., in reality farmers adjust fertilizer application to rainfall events in order to minimize losses, which is not implemented in the simulation model.

Management – Irrigation

The global irrigation map by Döll and Siebert [2000] contains information on the fraction of irrigated area within one five minute grid cell. For all 30 minutes grid cells that contain at least one 5 minutes cell irrigated by more than 1% we simulated irrigated yield. Irrigation was assumed to completely prevent water limitation on growth, therefore enough water was added at each time step to keep the soil water content at 100% field capacity.

Other management data

For other management events we made very simple global assumptions. It is assumed that 75 % of the shoot is removed at harvest as straw, and that cultivation events are restricted to one single ploughing just before planting. Ploughing events in DayCent affect decomposition rates of organic matter and further homogenise the ploughing layer with respect to soil texture.

3.6 References

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CHAPTER 4

Mapping global crop distribution

Summary

Global land cover patterns are accessible via remote sensing and ground truth data. Most approaches tend to characterize these land cover patterns, while more specific characterizations of large scale land-use patterns are scarce. In this study, we present a global map of crop distribution as an important aspect of agricultural land use. It represents the global distribution of 17 major crop types and grazing land for the early to mid 1990ies on a resolution of five arc minutes (app. 10 kilometers). For this purpose, we developed an allocation methodology which combines land cover characterization by remote sensing with census data on national and sub-national levels. The resulting crop distribution pattern provides a plausible and consistent representation of crop geography and is consistent with existing expert knowledge and other available data and information sources.

4.1 Introduction

Land use links human activities and the terrestrial environment. While land cover is defined as the "observed physical and biological cover of the earth's land, as vegetation or man-made features", land use is the "total of arrangement, activities and inputs that people undertake on a certain land cover type" [FAO and UNEP, 1999]. Large parts of the land surface are used for agriculture, forestry, settlements and infrastructure. This has vast effects on the natural environment: land use is the most important factor influencing biodiversity at the global scale [Sala et al., 2000]. Global biogeochemical cycles [McGuire et al., 2001; Priess et al., 2006a], freshwater availability [Rosegrant et al., 2002] and climate [Brovkin et al., 1999] are influenced by land use. In return, land use is itself strongly determined by environmental conditions. Climate [Mendelsohn and Dinar, 1999] and soil quality affect land-use decisions as they influence the suitability of land for specific crops and thus affect agricultural and biomass production [Wolf et al., 2003].

Studies dealing with the driving forces, mechanisms and impacts of land use and land-use change usually need spatially explicit data: the process of land-use change is location specific [Verburg et al., 2004] and scale dependent [Veldkamp et al., 2001]. Beyond, a spatial analysis of processes and impacts allows for an identification of hot-spots or regions of rapid change [Lepers et al., 2005]. Given the significance of spatial patterns in land-use science, it is crucial to characterise the current land-use distribution in order to initialise, calibrate or validate land-use models or to serve as an input for models dealing with biogeochemical cycles, land-use impacts or climate change. While for land cover, the upcoming use of remote sensing data boosted the ability to represent large scale land cover patterns [Friedl et al., 2002; Hansen et al., 2000; JRC, 2003; Jung et al., 2006; Loveland et al., 2000], the Science Plan of the "Global Land Project" [GLP, 2006] urgently expresses "the need for land use maps, especially at global and regional scales. Currently, most of the global mapping products are land cover classifications, with land use categories limited to cropland, pasture, and urban".

Based on this postulation, the objective of this study is to contribute to an improved characterisation of global land use by picking the most important land use type – agriculture – and disaggregating it to its major crop types, thus providing a global crop distribution map for a defined point in time.

Why would such a map be important? Obviously, the information where a specific crop is cultivated does not provide a complete characterisation of agricultural land-use. But combined with environmental information about soils and climate regimes, it facilitates the derivation of management characteristics such as planting and harvesting dates or the need for fertilisation and irrigation [Stehfest et al., submitted]. Detailed information on agricultural land-use practices and crop physiology is necessary to understand the broad range of environmental consequences. For example, the distinction between C_3- and C_4-based physiology of different crops is important in studies of the global carbon cycle [Lloyd and Farquhar, 1994; Still et al., 2003]. Donner and Kucharik [2003] discuss the importance of differentiating between maize and soybeans for quantifying nitrate export through the Mississippi River. Several large scale land-use models consider specific crops and allocate them in a spatially explicit way [ACCELERATES, 2004; Alcamo et al., 1998; Tan et al., 2003; van Meijl et al., 2006]. Such models could benefit from a spatially explicit data set in order to characterise the crop specific land-use distribution at a certain point of time. Other modelling studies claim the need for such data, e.g. large scale plant productivity models [Scholze et al., 2005] in order to test the large scale behaviour of their model.

To date, only one dataset of global extent provides this crop specific information: Leff et al. [2004] characterised global crop distribution for 18 crops on a five minutes latitude/longitude grid. For this purpose, they merged agricultural census data with a remote sensing product - in this case the IGBP-DISCover dataset [Loveland et al., 2000]. A first step had already been taken by Ramankutty and Foley [1998] who derived the fraction of cropland in a five minutes grid cell by calibrating the fraction of cropland represented by a 1km^2-IGBPDISCover-cropland-pixel against ground census data on national and sub-national level. Leff et al. [2004] derived the relative fraction of a crop within the total cropland of an administrative unit (national or sub-national). They assigned this fraction to every grid cell within an administrative unit and finally multiplied the fraction of the crop in the entire cropland with the fraction of cropland within the pixel as derived by Ramankutty and Foley [1998]. While many scientific approaches might require this type of information, other characteristics might be desirable for the application within global land-use models and thus motivate an alternative dataset of global crop distribution:

i) *Consistency with reported FAO areas*: many land-use models are driven by FAO data [Alcamo et al., 1998; Hughes et al., 2004]. Thus, it is useful if the actual areas represented by the crop distribution map agree with the reported FAO areas. Although calibrated against FAO data, the procedure of Ramankutty and Foley [1998] was not designed to achieve full agreement with FAO country data. Beyond, Leff et al. [2004] apply a 41x41 Gaussian filter on the borders of administrative units to smooth discontinuities which leads to further deviations from the FAO country totals.

ii) *Only one land-use type per grid cell:* There are two ways in assigning land-use information to grid cells: as fractional coverage (multiple land-use types per grid cell) or as dominant information (only one land-use type per grid cell). Both options have their pros and cons. The major advantage to employ dominant land use is its technical efficiency: working on a global five minutes grid already implies large amounts of data to be processed. This amount - as well as the degrees of freedom in allocating land use types - increases with the number of land-use types allowed per grid cell. Beyond, dynamic models dealing with biogeochemical and water cycles run into consistency problems when applied on a grid with (changing) sub-pixel information. The fractional information would then have to be aggregated to single input/output values. On the other hand, assuming dominant land-use results in somewhat artificial patterns by aggregating extensive or minor land-use types into a comparably small number of grid cells.

iii) *Conservation of sub-national crop distribution patterns:* Leff et al. [2004] combine the fraction of a crop within one sub-national administrative unit with the fraction of cropland per pixel (as given by Ramankutty and Foley [1998]). The resulting crop area within the sub-national unit does not necessarily represent its share in the countrywide area total of that crop. Or in other words: the relative distribution of a crop within a particular country (as given by the sub-national data) is not necessarily conserved. However, this is an important precondition to determine how the environmental impacts of land-use change are distributed in space.

Compared to Leff et al. [2004], this study aims to generate and provide a database of global crop distribution which meets the following criteria: **(1)** high spatial resolution (five arc minutes), **(2)** consistency with FAO country level data of arable land and permanent crops, specific crop areas and - in addition - grazing land, **(3)** dominant land-use types per grid cell in order to facilitate applicability in models of global biogeochemistry and hydrology, **(4)** representation of crop distribution patterns within countries as provided by sub-national census data; **(5)** enhanced use of sub-national data with respect to spatial coverage (new data for Africa, Europe, parts of South-East Asia and Latin America) as well as spatial resolution (high resolution county data for the USA, Australia and China); **(6)** quantitative evaluation by transparently comparing the mapping results against expert knowledge and the Leff et al. [2004] product.

In *chapter 4.2* we present the basic characteristics of the crop distribution map, the input data and the allocation algorithm. In *chapter 4.3*, we provide results in terms of global and regional maps and compare them against geo-referenced expert knowledge and against the Leff et al. [2004] dataset. Based on these results, we discuss the pros and cons of our methodology. In *chapter 4.4*, we conclude on the feasibility of our methodology, its relation to other available datasets and potential future improvements and research needs.

4.2 Materials and Methods

The objective of this study is to represent the global crop distribution for a defined point in time, based on data available from remote sensing and (sub-)national census. Concerning the land cover data derived from remote sensing, we decided to use the IGBPDiscover dataset for global land cover [Loveland et al., 2000] - for two reasons: first, we intended to provide direct comparability to the product of Leff et al. [2004] by using the same land cover data source - particularly since there is no evidence that other global land cover products are superior [Jung et al., 2006]. Second, most sub-national data are available for the early 1990s which coincides with the year 1992 which is represented by IGBP-DISCover, thus enhancing overall consistency. For these reasons we accepted the fact that the reference period (1991 to 1993) is over ten years back in time. More recent satellite derived products like GLC2000 lack corresponding sub-national land-use statistics, which are for most countries available until the mid 1990ies.

IGBP-DIScover with IGBP legend provides global coverage for 16 land cover types, including cropland and cropland/natural mosaic. The procedure to derive global crop distribution patterns is straightforward and consists of five steps: In **step 1**, we define the crop types considered in our analysis; in **step 2**, we derive the spatial extent of every crop on the country level and the spatial distribution of these country totals in sub-national administrative units; in **step 3**, we rank the five arc minutes grid cells, mainly according to their dominant land cover; in **step 4**, we allocate the areas from step 2, according to the ranking established in step 3; in **step 5**, we additionally allocate grazing land according to livestock density and land cover.

In the following paragraphs, we present these five steps in detail.

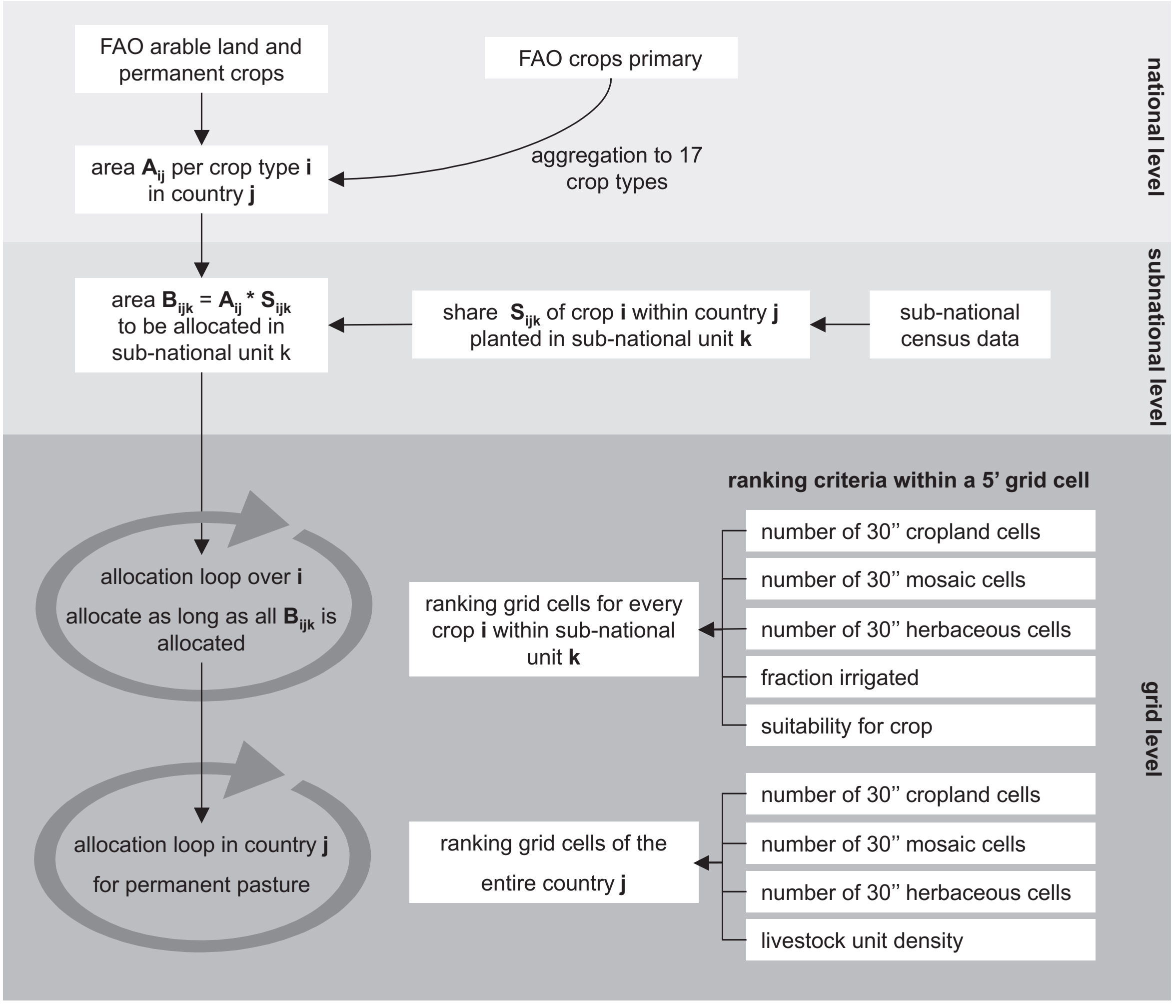

Figure 4.1: Methodology outline. The procedure includes the determination of crop areas on the national level, the derivation of sub-national distribution patterns and the grid based allocation within sub-national units. Grassland is allocated after crop allocation is completed.

Table 4.1: Major crop types represented in the map and the most important FAO equivalents

Crop type	Main FAO crops
wheat	wheat
other temperate cereals	barley, oats, rye, buckwheat
rice	paddy rice
maize	maize
other tropical cereals	millet, sorghum, quinoa
pulses	dry beans, dry peas, chick peas, lentils
temperate roots and tubers	potatoes, sugar beets
tropical roots and tubers	cassava, sweet potatoes, yams
annual oil crops (excl. soybeans)	groundnuts, rape, sesame, sunflower
soybeans	soybeans
permanent oil crops	oil palm, coconut, olives
vegetables	see FAOSTAT for details
fruits	see FAOSTAT for details
sugarcane	sugarcane
fiber crops	cotton seed, hemp, flax
coffee and cocoa	coffee, cocoa
other stimulants	tea, tobacco

1) Aggregation of crop types: Crops were aggregated to major crop categories (*crop types*). This aggregation took into account several criteria, including i) global significance with respect to spatial extent (e.g. wheat was considered a single category due to its large significance), ii) similarity in eco-physiological characteristics (assimilation type, phenology, phylogenetic affinity), and iii) similarity of intended use. We finally defined 17 major crop types which are listed in table 4.1. For national as well as sub-national census data, the crop areas were aggregated according to these categories.

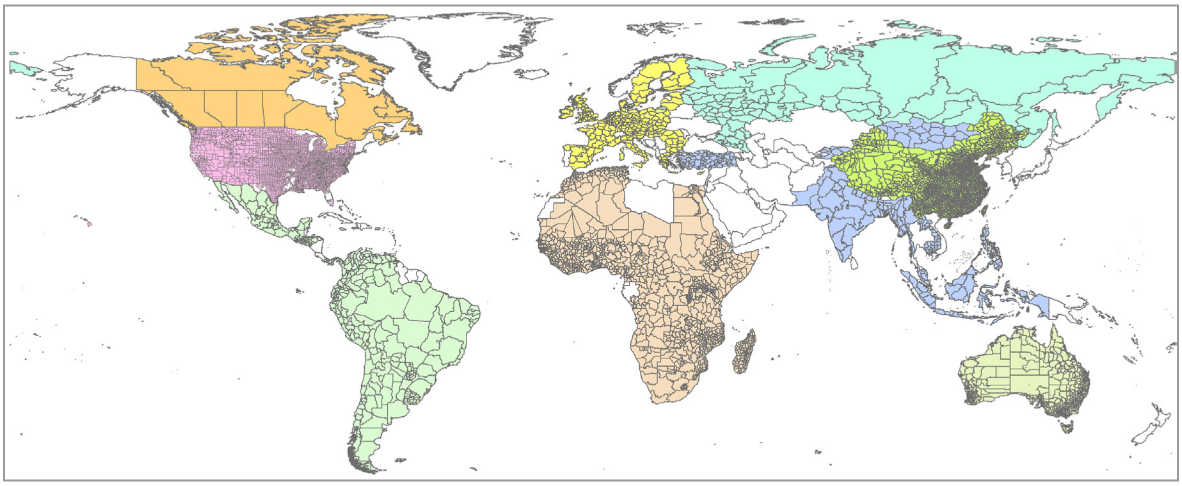

Figure 4.2: Coverage and resolution of sub-national census data to derive sub-national crop distribution patterns. Homogeneous colours indicate homogenous data sources.

2) Calculation of areas to be allocated: For every country, we allocated the complete cropland area as reported by FAO [2005]. Though aware of the fact that the FAO data are flawed with high uncertainties and inconsistencies [ABCDQ, 2005; McCalla and Revoredo, 2001; van Woerden, 1999; Young, 1999], our aim was to generate a spatial dataset which is fully consistent with FAO data (see chapter 4.3 for a discussion of shortcomings of this approach). The total cropland area allocated per country was calculated as the 1991-93 mean of *arable land and permanent crops*. The total area per crop type was then derived by the share of the respective crop type in the area sum of all crop types (which is not necessarily equal to *arable land and permanent crops* due to multi-cropping or fallow periods[a]). As a next step, we evaluated the spatial distribution of a crop *within* the country: sub-national census data were applied to derive the share of the country's crop area which is planted in an individual administrative unit. This procedure was chosen for two reasons: i) in order to deal with the inconsistencies between the areas reported by FAO and by the various sub-national datasets ii) to account for the fact that the sub-national data was not always representing the reference period of 1991-93. The outcome of this step corresponds to the area B_{ijk} in figure 4.1, i.e. the area of each *crop type i* to be allocated in *sub-national unit k* of *country j*. Table 4.2 provides a full list with sources of sub-national data, their administrative level and the temporal coverage. If temporal coverage of the sub-national data was not within 1991-93, we chose the years closest to this time slice to calculate the value B_{ijk}. Additionally, figure 4.2 provides an illustration of the sub-national data coverage and its spatial resolution.

[a] If there is more than one harvest per year, the harvested areas are accordingly accounted more than once. In contrast, temporary fallows are accounted for by "arable land", but not by harvested areas (see FAO, 2005).

Table 4.2: Sources of sub-national input data and their administrative and temporal reference

Region/country	Source	Administrative level	Time period
Africa	FAO, 2004	1st level	1989-2000
Australia	ABS, 2000	county (2nd level)	1991-95
Bangladesh	GIEWS, 2005	1st level	1993-94
Cambodia	GIEWS, 2005	1st level	1996-97
Canada	StatCan, 2005	Province level (1st)	1996
China	Verburg et al, 1999	County level (2nd)	1991
European Union	EUROSTAT, 2005	2nd level (NUTS2)	1994-96
India	GIEWS, 2005	State level (1st level)	1994-95
Indonesia	GIEWS, 2005	1st level	1993
Kyrgyzstan	GIEWS, 2005	1st level	1995
Laos	GIEWS, 2005	1st level	1998
Latin America/Caribbean	GIEWS, 2005	2nd level	1989-94
Malaysia	GIEWS, 2005	1st level	1993
Mongolia	GIEWS, 2005	1st level	1995
Myanmar	GIEWS, 2005	1st level	1994-95
Nepal	GIEWS, 2005	1st level	1994-95
Pakistan	GIEWS, 2005	1st level	1993-94
Philippines	GIEWS, 2005	1st level	1990
Russia	USDA, 2004	Oblasts (1st level)	1990-95
Turkey	GIEWS, 2005	1st level	1995
USA	USDA, 2005	County level (2nd)	1991-95

3) Ranking of cells within the administrative units: The grid cells within one administrative unit were ranked according to the following criteria: number of 30 arc second *cropland* cells within one five arc minute cell (from IGBP-DISCover/IGBP legend, Loveland et al., 2000); number of 30 arc second *natural/cropland mosaic* cells; number of other cells with potential misclassification (such as grassland, shrubland); fraction of irrigated area within a five minute grid cell [Siebert et al., 2002]; suitability for the specific crop according to the GAEZ methodology [Fischer et al., 2002]. Table 4.3 provides the list of global input grids considered in this analysis. The ranking is based on the following three assumptions:

Some land cover types are particularly susceptible to misclassification: It is assumed that cropland is more likely to be misinterpreted as another herbaceous land cover than as other land cover types such as forest [Jung et al., 2006]. Thus, if no more cells with dominant agricultural land cover are available, the allocation algorithm prefers grasslands and shrublands over forests, barren lands or wetlands.

Irrigation is an indicator of agricultural activity: This assumption is more or less self-evident. The map of irrigated areas [Siebert et al., 2002] provides additional independent information of the spatial distribution of (irrigated) cropland. Since the map is representative for the irrigated area in the mid 1990s, it is used as an additional indicator of cropland.

Crop suitability is an important determinant of the distribution of agricultural land: The global patterns of crop distribution agree significantly with patterns of crop suitability. Although this study intends to derive crop distribution patterns mainly based on census and remote sensing data, the consideration of crop suitability patterns still makes sense: If the above ranking criteria do not yield a unique solution, it is still more likely that a crop is found on an environmentally suitable location than on an unsuitable location [Grigg, 1995; You and Wood, 2004]. However, this assumption particularly affects the resulting crop distribution patterns in countries without any sub-national data and a rather homogeneous distribution of agricultural land cover (such as New Zealand or Japan).

As already pointed out, the primary goal was to map global crop distribution by fusing census data with remote sensing data. Thus, we do not consider the above input layers as equally important. Quite the contrary, we consider the land cover data from remote sensing as the dominant indicator of the location of cropland within a sub-national unit. Only if the use of land cover classification does not provide a unique location preference, we apply the irrigated area as a further indicator of agricultural area. And only if that procedure does not yield a unique location preference, the crop suitability according to GAEZ is applied for further ranking. This hierarchical procedure allows a differentiated preference ranking within a sub-national unit while minimising modelling assumptions. The reasoning is to prefer "measured" indicators (i.e. remotely sensed data) over "modelled" indicators (such as the crop suitability according to GAEZ) and "actual indicators of location" over "potential indicators of location". In other words, we assign different degrees of "reliability" according to how the data was generated.

Table 4.3: Global input grids used for grid cell ranking

Theme	Source	Spatial resolution	Comments
Land cover	IGBP-DISCover, [Loveland et al., 2000]	30 arc seconds	contains 16 land cover types for the IGBP legend
Irrigated areas	Siebert et al. [2002]	5 arc minutes	provides a fraction of irrigated area within one grid cell
Crop suitability	Global Agroecological Zones model, [Fischer et al., 2002]	5 arc minutes	available for different crops: wheat, maize, roots and tubers, pulses, oil crops, cotton, rice
Livestock density	Siebert [2005]	2.5 arc minutes	in terms of ruminant livestock (cattle, sheep and goats, camels, buffaloes)

4) Allocation of crop areas to grid cells: According to the preference ranking, crop cells were allocated within one administrative unit k until the area of crop i (as calculated in *step 2*) was met. The areas as derived from census data were imperatively allocated. If no sub-national data was available, cells were allocated within the entire country according to the preference ranking. The allocation was organised as an iterative procedure, assigning a certain amount of N_i cells to every crop type i during each iterative step. This amount depends on the share of area B_{ijk} (see figure 4.1) within the entire crop area of the administrative unit k and on the total number of cells N_k within the administrative unit k, but was constrained to a maximum of ten cells per crop type and iterative step (ad-hoc value).

$$N_i = \min\left(floor\left(\frac{B_{ijk}}{\sum_i B_{ijk}} N_k \right), 10 \right) \qquad \text{Eq. 4.1}$$

The reasoning behind this procedure was to avoid biases: small administrative units might not have enough space for all crop areas calculated in step 2 (due to inconsistent or flawed input data). In such a case, the procedure reduces an overrepresentation of minor crops within that particular administrative unit. Accordingly, it avoids an overrepresentation of minor crops on very suitable agricultural land. Data inconsistencies might implicate that not all areas for each crop could be allocated for each and every administrative unit. Beyond, the discrete character of the allocation might cause allocated areas to be higher than calculated (nominal) areas. In both cases, deviations from the "allocation target" were memorized and allocated in the neighbouring administrative unit.

5) Allocation of grazing land: In the final step, grazing land was allocated, based on the areas given by the FAO land use category *permanent pasture.* For this purpose, the ranking for agricultural crops from step 3 was slightly modified: Irrigated area was not considered as an indicator of grazing land and instead of using crop suitability as a criterion, we ranked the grid cells according to their livestock unit density, i.e. the number of livestock units per unit area. A global map of livestock unit density was derived by converting global gridded data [Siebert, 2005] of ruminant stocking rates (cattle, sheep, goats, camels, buffalos) to livestock units. The conversion was based on regional conversion factors as given by Seré and Steinfeld [1996]. Using the preference ranking, grazing land was allocated over the entire country and not within sub-national units (due to the lack of sub-national distribution data for most countries). However, the grids of ruminant stocking rates [Siebert, 2005] were derived from sub-national data, so we implicitly take sub-national census data into account. Note that assuming livestock unit density to indicate the location of grazing land is a rough simplification: Particularly in industrial (or landless) production systems, livestock density is largely decoupled from grazing land [Seré and Steinfeld, 1996]. Thus, the assumption particularly holds true in countries with rather extensive livestock management systems (i.e. most poor countries, but also some industrialised countries such as the USA or Australia).

4.3 Results and Discussion

In this section, we present some of the results of mapping the global distribution of 17 major crops. First, we present global maps for wheat, maize, soybeans, rice and grazing land (figure 4.3). Presenting the example of Australia, we show the effect of using dominant land use types per grid cell as compared to using fractional values (figure 4.4). Leff et al. [2004] already pointed out that it is difficult to evaluate such a global dataset, since virtually no independent reference data is available. We tried to evaluate the quality of our dataset by applying two different strategies:

1) Comparison to independent expert knowledge: We compare our results to regional maps of major and minor growing regions of specific crops. These maps were provided by the FAO Global Information and Early Warning Systems [GIEWS, 2005]. For seven crops in nine regions we analyse how the crop cells of our map coincide with the major and minor growing regions. Although this procedure is not a strict evaluation of data quality, it provides a quantitative measure of agreement between the two data sources.

2) Comparison to Leff et al. [2004]: The basic differences between our approach and Leff et al. have already been sketched in chapter 4.1. Leff et al. [2004] calculate fractional crop coverage within grid cells and are not necessarily consistent with FAO country level data. This complicates a map comparison. Nonetheless, it is also possible to compare fractional against categorical data, defining the agreement between two cells as the minimum fractional value of the two input maps. For map comparisons, we apply a methodology provided by Pontius [2002] in order to quantify map agreement at multiple resolutions.

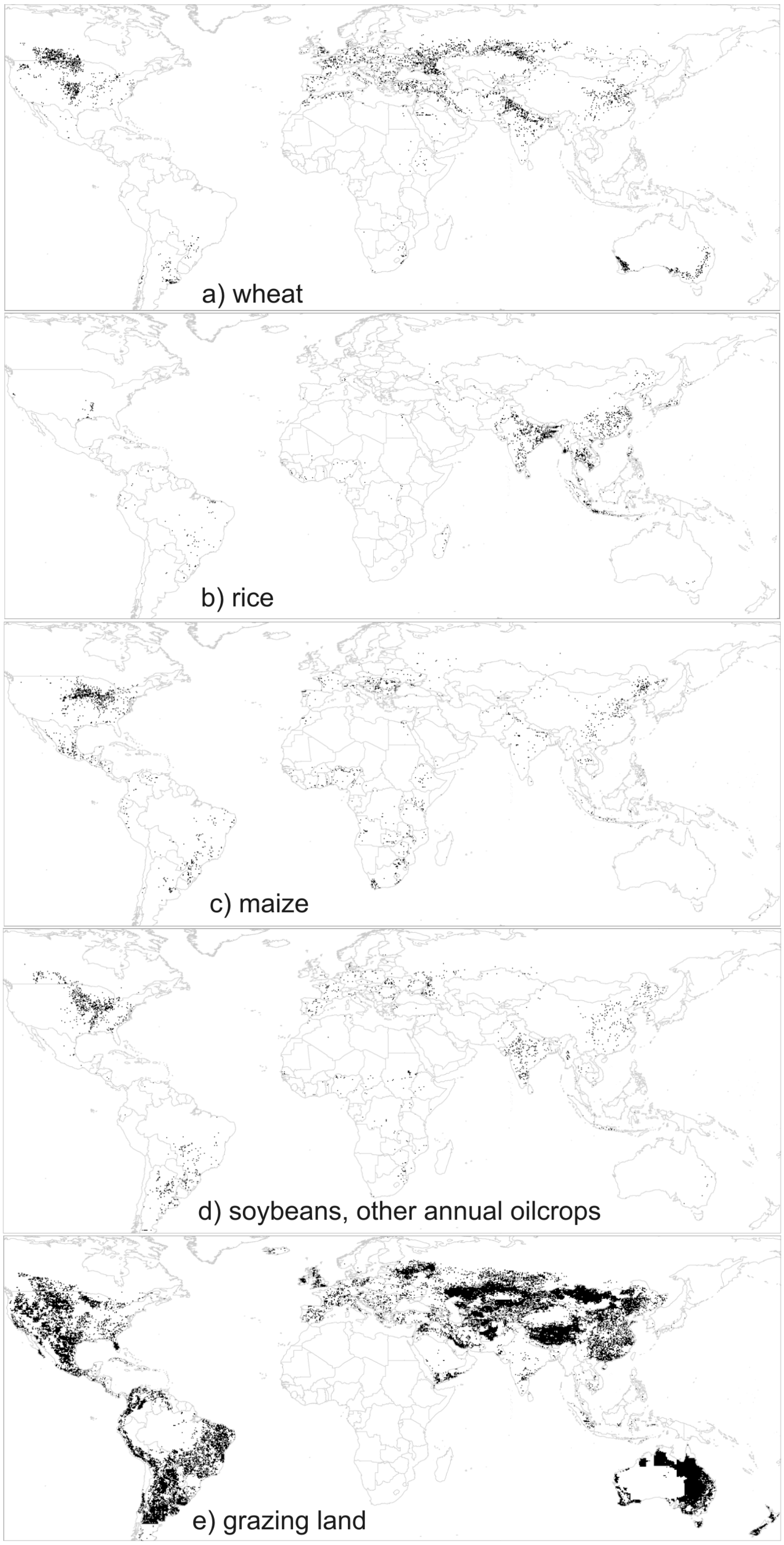

Figure 4.3: Example maps of global crop distribution; **a)** wheat, **b)** rice, **c)** maize, **d)** soybeans and other ann. oil crops, **e)** grazing lands. Note that map e) only indicates the occurrence of grazing, not the intensity.

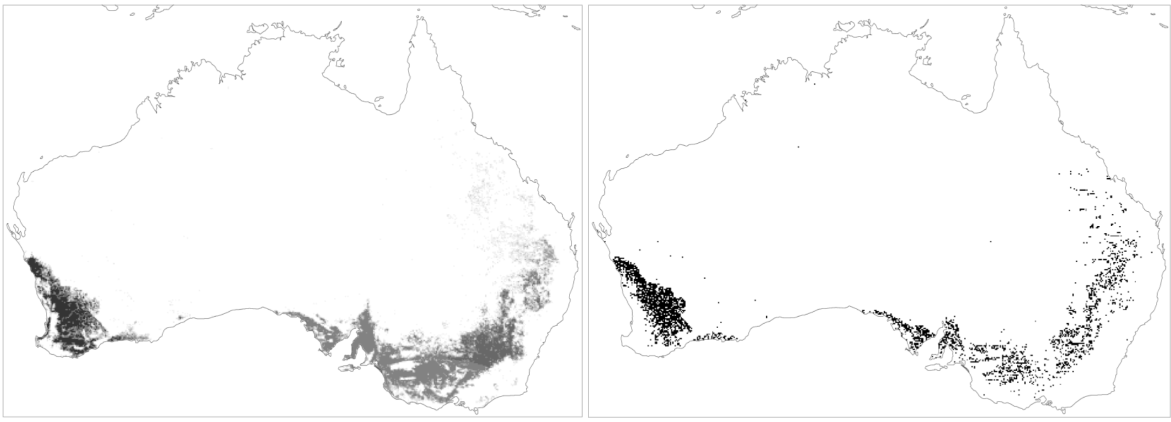

Figure 4.4: Effect of dominant vs. fractional definition of land use types; example for wheat in Australia (**left:** fractional coverage from Leff at al. (2004), greyscales represent fraction of coverage; **right:** dominant wheat cells). Both figures represent almost identical country totals.

Comparison to GIEWS growing areas

The GIEWS maps of major and minor growing areas are available digitally only for a few countries and crop types. Thus, we can show only examples of agreement between GIEWS maps and our product. For seven crop types in nine regions or countries, we calculated the share of grid cells which falls in major or minor growing areas, respectively. Some regional map segments are shown in figure 4.5. Table 4.4 provides quantitative results of the map comparisons.

It can be seen that for the selected examples the share of crop area allocated within the major growing areas mostly makes up for more than 50 percent of the total area of that crop within the respective region. Only for maize in China and Argentina, the share is lower (44.3 and 42 percent, respectively). Thus, for the selected map segments the major growing areas seem to be widely consistent with our crop distribution map. However, significant shares of crop areas in our map seem to be located outside even the minor growing areas as given by GIEWS (e.g. for rice and wheat). Unfortunately, GIEWS does not specify its definition of “major/minor growing area” which means that these quantitative results could not be further evaluated. Altogether, the limited number of examples does not allow a general evaluation, but the fractions of all crops (except rice in SE-Asia) follow the expected pattern of allocation in the order: major cropping area > minor cropping area > rest of the country.

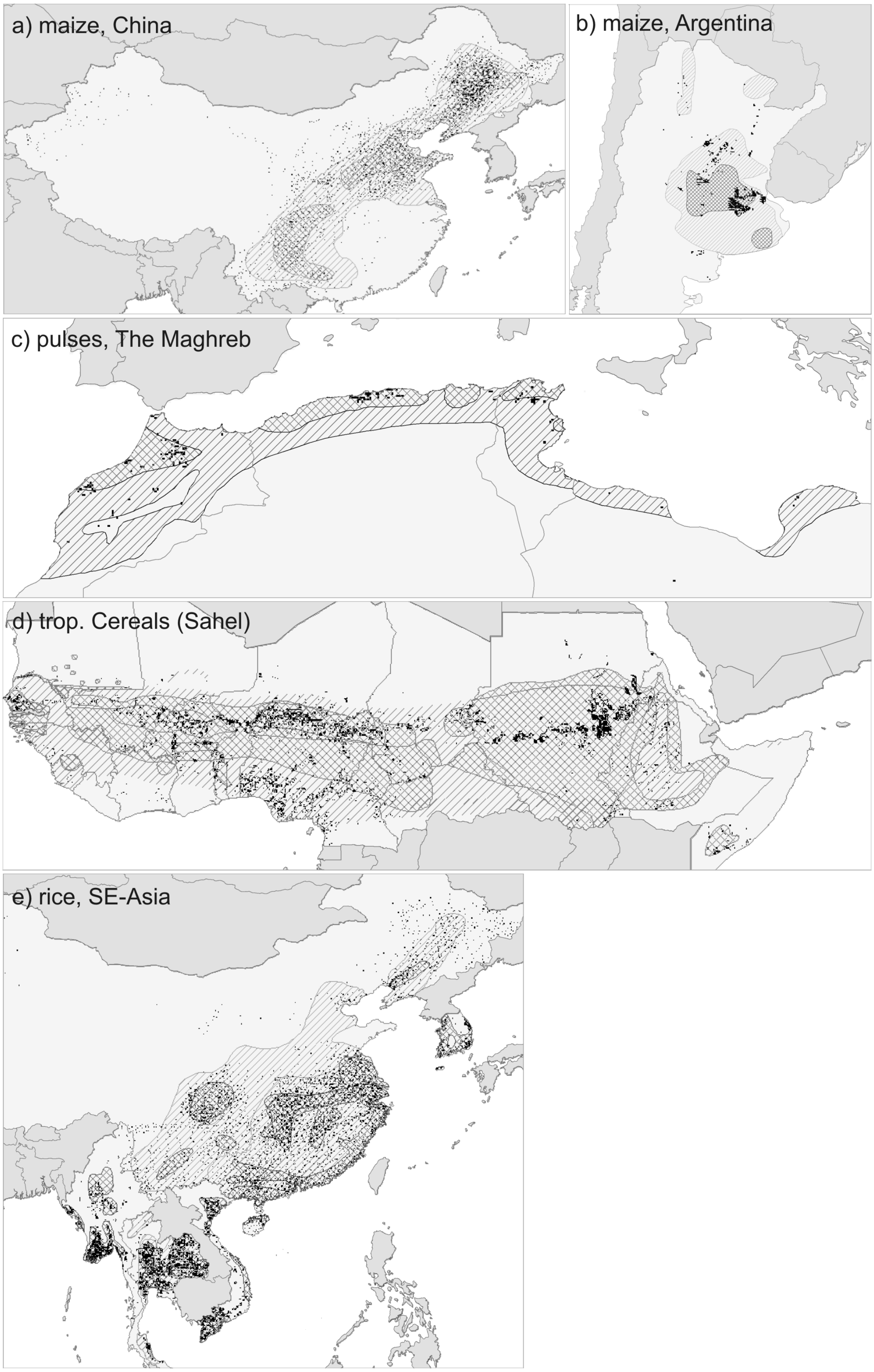

Figure 4.5: Map segments of GIEWS growing areas and our crop distribution map. black: crop cell, cross-hatched: major growing areas, hatched: minor growing areas

Table 4.4: Map comparison of GIEWS maps and our product

Crop	Region/Country	Percent in major growing area	Percent in minor growing area	Remaining percentage
Maize	China	44.3	37.6	18.1
Maize	Argentina	42.0	43.6	14.4
Tropical Cereals	Sahel[1)]	72.1	22.9	5.0
Cotton	India	65.3	*not available*	34.7
Pulses	African Mediterranean Coast[2)]	61.5	34.3	4.2
Rice	South-East Asia[3)]	52.0	19.3	28.7
Sugarcane	Mexico	60.6	*not available*	39.4
Wheat	Ethiopia	51.8	23.5	24.7
Wheat	Near East[4)]	72.2	*not available*	27.8

1) Somalia, Kenya, Sudan, Central African Republic, Chad, Niger, Nigeria, Burkina Faso, Mali, ...
2) Morocco, Algeria, Tunisia, Libya
3) China, Thailand, Vietnam, Myanmar, South Korea
4) Turkey, Syria, Lebanon, Israel, Iran, Iraq, Jordan

Comparison to Leff et al.

We compared the Leff et al. [2004] map against our map for eight single crop categories (maize, soybeans, cotton, cassava, pulses, rice, wheat, potatoes). In addition, we calculated map agreement on several spatial resolutions. This was to identify the impact of resolution on map agreement. For details about the methodology see Pontius [2002]. To derive coarse resolution maps, we calculated the fraction of each crop category within a lower resolution grid cell, derived from the original five minute resolution maps. Based on that procedure, agreement at a specific resolution can be defined as follows:

$$\textit{total agreement at resolution } g = \frac{\sum_{n=1}^{Ng}\left[Wn\sum_{j=1}^{J} MIN(Rn, j, S, n, j)\right]}{\sum_{n=1}^{Ng} Wn} \qquad \textit{Eq. 4.2}$$

j	:	*category (1 ...J)*
Rn,j	:	*the proportion of category j in grid cell n of map R*
Sn,j	:	*proportion of category j in grid cell n of map S*
Ng	:	*number of grid cells in the map at resolution g*
Wn	:	*number of fine resolution cells that make up a coarse resolution cell*

Kappa statistics were derived for each of the eight crops at the base resolution and at twice-, four-, six-, twelve- and 60 times the base resolution. The results in figure 4.6 show the changes in Kappa for the multiple resolutions (note that the x-axis only extends up to 30 times the base resolution in order to better show the behaviour of the curves within this range).

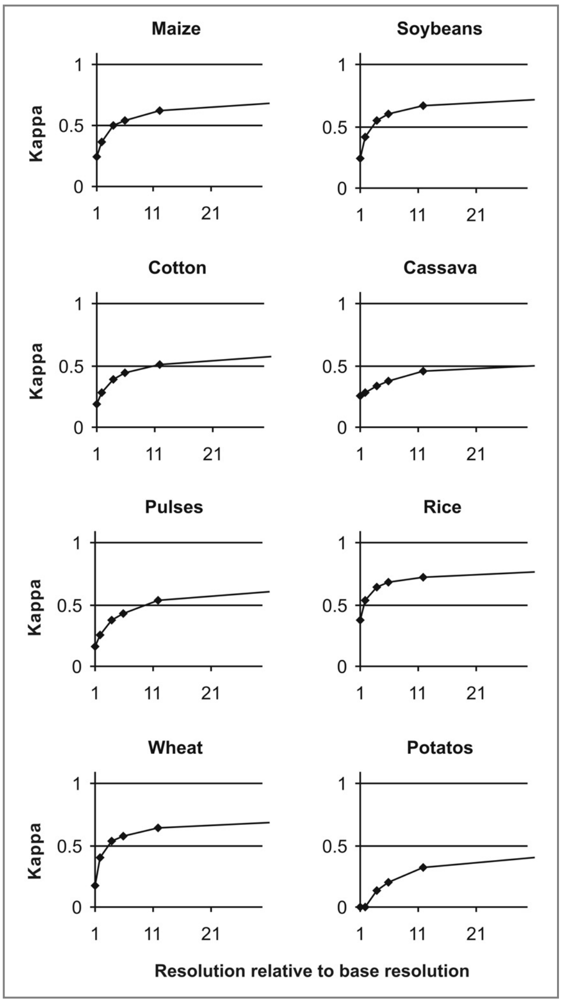

Figure 4.6: Results of map comparison between Leff et al. (2004) and the present study for multiple resolutions. Graphs show map agreement in terms of Kappa (as shown on the y-axis) for 8 different crops at 6 different resolutions (as shown on the x-axis). Note that the x-axis only extends up to 30 times the base resolution in order to better show the behaviour of the curves within this range.

One should act with caution when comparing the two maps by standard methodologies of map comparison. Such a comparison cannot be considered a validation, since in many respects the two studies employ similar data sources. Nevertheless, a number of conclusions can be drawn from the comparison: at the working resolution of five arc minutes, the agreement is generally fair or less than fair.[b] This has to be attributed to the different mapping methodologies and the fact that our product employs categorical data. However, the agreement between the two maps increases significantly with decreasing resolution. The threshold for moderate agreement is reached at a resolution 2-4 times lower than the original, substantial agreement is reached at a resolution of about 30 to 60 arc minutes while some crops reach a level of "almost perfect agreement" at resolutions about 60 times higher than the original five arc minutes. Generally, the agreement is

[b] Landis and Koch [1977] employed a qualitative evaluation of Kappa values as follows: poor (< 0), slight (0 - 0.2), fair (0.2 - 0.4), moderate (0.4 - 0.6), substantial (0.6 - 0.8), almost perfect. (0.8 - 1).

higher for crops which are more wide-spread (maize, soybeans, wheat, rice) while e.g. for potato and cassava the agreement is rather low. Of course, the substantial agreement at higher resolutions is not too surprising since both methodologies employ similar data sources. Rather interesting is the remaining level of disagreement even at very coarse resolutions. First, this has to be attributed to the allocation methodology which restricts minor crops to a small number of grid cells. Secondly, the differences in sub-national data sources can cause different large scale patterns (we have entirely new coverage for Europe, Africa, large parts of Latin America and large parts of South-East Asia and higher resolution data for the US, Australia and China). And finally, the total crop areas differ because FAO area totals are imperatively allocated in our approach.

Further discussion

As pointed out, the basic problem in evaluating the quality of this dataset is the lack of appropriate reference data for validation - particularly in terms of geo-referenced datasets which allow standardised map comparison procedures. The comparison to the Leff et al. [2004] reveals fundamental discrepancies at the base resolution and a significantly increasing agreement with lower resolutions. But still, differences remain at coarse resolutions of even 60 times below base (corresponding to about 500 km at the equator).

Assigning only a single crop type per grid cell instead of allowing multiple crop types makes the resulting crop distribution more artificial. Whether this has to be considered disadvantageous or not depends on the application context.

Apart from the methodological aspects, the basic source of error is the underlying data, mainly the IGBP land cover classification, the FAO national level census data and the various sub-national data sets. A systematic and quantitative evaluation of these input data is beyond the scope of this study. Defries and Los [1999], Jung et al. [2006] and Scepan [1999] provide an evaluation for the land cover data, while ABCDQ [2005], van Woerden [1999] and Young [1999] discuss the quality of the FAO country level data. For the sub-national data, virtually no information about data quality was available.

A major limitation of the present map is the lack of agricultural management information beyond the dominant crop. This includes e.g. the aspects of *crop rotations*, *multiple cropping* and *irrigation*. Information about typical rotations is not provided in our map, although crop rotations may have important effects on soil nutrient cycles [Priess et al., 2006a] and pest management [Abate et al., 2000; Helenius, 1997]. *Multiple cropping,* particularly in terms of sequential cropping, notably influences the productivity of land. In subtropical and tropical regions, up to three growth cycles per year are possible - adequate management presumed [FAO, 2002]. On the other hand, multiple cropping might lead to an accelerated exhaustion of soil nutrients and thus soil degradation [Priess, 2006b]. Thus, this issue is closely linked to the management of on-site nutrient cycles. As for *irrigation*, it was already pointed out that there is a spatially explicit data representing the global distribution of irrigated areas. However, it would be useful to generate crop specific information of irrigated areas. This is because crops react differently to water stress and - more important - crops differ in transpiration rates and thus crop water demands [Allen et al., 1998].

4.4 Summary and Conclusions

Assessments of global change urgently need spatially explicit land-use data with global coverage. There are several products available for global land cover patterns which delineate agricultural from non-agricultural areas. However, more detailed characterisations of agricultural land use (e.g. in terms of cultivated crops) are still missing. To date, there is one data set characterising the global crop distribution on a grid of five arc minutes resolution [Leff et al., 2004]. We offer a new data set as a product with alternative features: **(1)** representation of one crop type per grid cell (dominant crop type) instead of fractional crop coverage per grid cell. This makes the resulting distribution patterns more artificial, but bears advantages for the application within global models, particularly in terms of nutrient flux calculations and run-time efficiency; **(2)** consistency of pixel information with FAO country level data about agricultural areas and cultivated crops; **(3)** consistent representation of crop patterns as given by sub-national datasets; **(4)** additional representation of grazing land based on data about country level grazing areas, a spatial dataset of livestock density and the distribution of land cover types suitable for livestock grazing; **(5)** increased coverage and resolution of sub-national data, e.g. by including additional data from Europe, Africa, Latin America and South-East Asia and by using higher resolution data for the USA, Australia and China.

Quantitative evaluation of the resulting map is difficult because of the lack of appropriate reference data. However, the product is widely consistent with available expert knowledge as provided by USDA and GIEWS. The pixel-by-pixel comparison with a modified version of the Leff et al. [2004] map resulted in fair agreement. However, the agreement at lower resolutions (approximately 30 to 60 arc minutes) is substantial, indicating a good agreement of large scale patterns. Nonetheless, differences remain even at coarse resolutions due to differences in input data and allocation methodologies.

The representation of global cropping patterns is considered a major step forward as compared to the exclusive use of remotely sensed land cover patterns. We consider it a first step towards a more system-based characterisation of agricultural land use. Such a characterisation might not only include major crop types, but also typical crop rotations, occurrence of multiple cropping, input levels of irrigation water, fertiliser and other agrochemicals. Qualitative information on these issues have partly been provided by Dixon et al. [2001] for developing countries. However, it remains a challenging task to transfer this information to the grid level and to merge it with quantitative data sets in order to serve as an input to global scale assessments.

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CHAPTER 5

Modelling the spatio-temporal distribution of irrigated areas in Africa

Summary

Irrigation contributes to global food security, but also accounts for most of the human freshwater consumption and a range of adverse environmental impacts. In the next 50 years, irrigated areas are expected to continue to expand. In this study, we develop a methodology to simulate the spatio-temporal distribution of irrigated areas. This methodology is implemented in the global land-use change model LandSHIFT. Simulated changes in irrigated areas are exogenously driven by food demands, general trends in irrigation expansion and technological development. The spatial allocation of irrigated areas on a five arc minutes grid is governed by a set of spatial factors such as river network density or terrain slopes. We explicitly include the dynamic feedback of water scarcity on the distribution of additional irrigated area. The methodology is tested and applied in an exemplary simulation experiment for the African continent. The model succeeds in representing the general suitability patterns for irrigation in Africa (using the ROC method as a validation technique, we achieve ROC values between 0.67 and 0.79). Our analysis suggests that there is still potential to expand irrigation in parts of Africa, while some regions and basins are likely to face increasing water stress.

5.1 Introduction

Irrigation considerably contributes to world food production. In developing countries, irrigated land accounts for only 20 % of the total arable area. But due to higher yields and more frequent harvests, it supplies 40 % of the crop production and close to 60 % of the cereal production [FAO, 2002]. On the other hand, irrigated agriculture is by far the most important water user in the world: it is responsible for over 70 percent of all water withdrawn for human use [Shiklomanov, 2000]. Adverse environmental impacts of irrigation can comprise salinisation and water-logging of soils, the pollution of surface and groundwater resources [Chhabra et al., 2006], or even large scale desertification processes [Saiko and Zonn, 2000] (see Trout [2000] and Dougherty and Hall [1995] for an overview). Globally, the extent of irrigated areas almost doubled within the last 40 years and, according to FAO projections, will expand by another 40 percent within the next 30 years [FAO, 2002].

Concerning the expected expansion of irrigated areas, Africa has attracted particular attention: food production in Africa has not kept pace with population growth during the last 40 years [FAO, 1997] and parts of Sub-Saharan Africa regularly suffer drought-related famines [Brooks, 2004; Heimo, 2004]. The expansion of irrigated agriculture is considered as one strategy to improve food security in parts of the continent. FAO [2002] expects irrigated areas in Sub-Saharan and Northern Africa to expand by 25 to 30 percent by 2030. Although Africa only accounts for five percent of the global irrigated area, irrigation already makes an essential contribution to crop production in many African countries, namely in Northern Africa (le Maghreb, Egypt, Sudan) or in South Africa. In the last 40 years, irrigation expansion facilitated a major share of yield increases in Africa (figure 5.1). While in the humid parts of the inner tropics (e.g. the Congo basin) crop yields are generally not water limited, experts still see potential for irrigation to enhance productivity in other regions, namely in parts of the Sahel, Eastern and Southern Africa [Kandiah, 1997; Purcell, 1997]. The currently low development of water resources in these parts of Africa is mainly a consequence of high irrigation investment costs coupled with declining world prices for food and the failures of many past irrigation projects [IWMI and CGIAR, 2004]. Rosegrant et al. [2005] also consider insecure land tenure regimes as a limitation to irrigation development. Additionally, the potential of irrigation to contribute to agricultural development is limited by growing scarcity of water resources and increasing competition from other water using sectors such as households or industry [UNEP, 2002; Vörösmarty et al., 2005].

From the perspective of *Earth System Science*, irrigation forms a major interface between land and water use. The science plans of both the Global Land Project [GLP, 2006] and the Global Water System Project [GWSP, 2006] address the issue of irrigation: While the GLP stresses the role of irrigation in agricultural land management and intensification in order to meet growing crop demands, the GWSP rather focuses on the aspect of river basin management, the competition between different water using sectors and impacts on regional hydrological regimes. These aspects call for an integrated consideration. But while there is at least one continental to global scale *hydrological model* which explicitly considers the role of irrigation in water consumption [Alcamo et al., 2003; Döll and Siebert, 2002], large scale *land-use models* mostly ignore changes in irrigated areas: according to Heistermann et al. [2006], only few continental to global scale land-use models explicitly include irrigation in their production function, however, dynamic changes are neglected and water resources are rather not related to environmental processes. The IMPACT-Water model

[Rosegrant et al., 2002a] is one of the few models which endogenously calculates changes in irrigated areas, however, as an economic partial equilibrium model for the global agricultural sector, it operates on the aggregated basis of 36 world regions. This is too coarse a basis for taking into account the geographic variability of water and land constraints to irrigation.

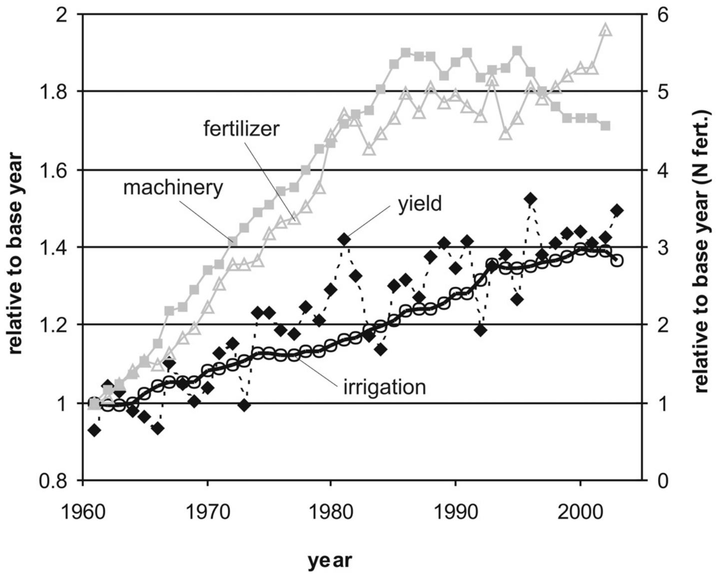

Figure 5.1: Agricultural intensification in Africa. Though Africa lags behind other world regions in boosting crop yields, figures suggest a relationship between increasing crop yields and management inputs over the last 40 years. This figure is for illustrative purposes, only. It shows the relative increase in cereal yields (black rhombi), the ratio between irrigated area and arable land (black circles), kg N fertilizer per ha (grey triangles), and tractors per ha (grey rectangles) – all relative to 1961 -1965 averages. We assume that all management inputs together facilitated the yield gains, including a significant effect of irrigation expansion.

Nonetheless, previous studies provide valuable information and methodologies to assess the potential for irrigated cultivation on large spatial scales. For example, FAO [1997] assesses the upper limit for irrigation expansion in Africa on a basin level: the approach considers soil and slope constraints and additionally assumes that the entire renewable freshwater resources in a river basin are available for irrigation water consumption. Fischer et al. [2002] evaluate the contribution of soil and terrain characteristics to irrigation potential, while Cassel-Gintz et al. [1997] assess the "potential irrigation capacity" of a grid cell by applying a fuzzy-logic based evaluation of slope and river networks. However, both Fischer et al. [2002] and Cassel-Gintz et al. [1997] ignore water availability as a limiting factor. All three approaches apply expert knowledge in order to quantify the limitation which a particular landscape property exerts on the irrigation potential of specific locations. They do not consider the actual distribution of irrigated areas and therefore do not to consider how this distribution is actually constrained by the aforementioned environmental factors. Actually, irrigation is not necessarily applied on locations which are technically optimal or adequate for sustainable soil management. Neither are the water consumption rates for irrigation always compatible with the concept of sustainable river basin management [FAO, 1997; Vörösmarty et al., 2005].

In this study, we will introduce a methodology to simulate the spatial dynamics of irrigated areas and apply it to Africa. This methodology is integrated in the LandSHIFT model[a] which is a framework for modelling continental to global scale land-use changes and is introduced by [Alcamo and Schaldach, 2006; Schaldach et al., 2006]. To simulate changes in the distribution of irrigated areas in Africa, we apply a rule-based modelling approach. The spatial dynamics are

[a] **Land** **S**imulation to **H**armonize and **I**ntegrate **F**reshwater Availability and the **T**errestrial Environment

governed by the multi-criteria evaluation of properties on landscape and basin level. Innovative aspects are:

- the introduction of transparent, flexible, scale-sensitive and data-driven methods to evaluate the factors that influence the spatial distribution of irrigated areas. Our approach is parameterised and calibrated with a minimum of assumptions. At the same time, it allows users to explore the impact of second order assumptions, e.g. by modifying suitability relations.
- the consistent simulation of dynamics in both rain-fed and irrigated cultivation in a large-scale land-use model
- consideration of water availability as a constraint to the expansion of irrigated areas: we account for both the *availability of renewable freshwater resources* and the *actual water consumption per river basin*. In every time step, we quantify the increase in water consumption caused by additional irrigated area and subsequently evaluate the implications for further expansion of irrigated areas.

The presented methodology can be used to address questions such as: how will the spatial distribution of irrigated areas change under growing demands for food? How strong will water scarcity influence future distribution patterns of irrigation, and inversely: how will the pattern of irrigation change affect water scarcity? How will these developments differ under different general trends in irrigation expansion? As an example how these questions can be addressed by our methodology, we simulate changes in irrigated areas in Africa over the next 50 years under different scenarios of irrigation expansion and different assumptions on the limiting impact of water scarcity on irrigation expansion.

In chapter 5.2, we give a short overview of the LandSHIFT modelling framework (5.2.1), then describe the methodology to simulate changes in irrigated areas and its integration in LandSHIFT (5.2.2-5.2.3), and finally outline the simulation experiment for the African continent (5.2.4). In chapter 5.3, we present and discuss the results of this application. Chapter 5.4 gives our conclusions and an outlook on future research with respect to model testing, improvement and potential applications.

5.2 Materials and Methods

5.2.1 The LandSHIFT Model

Our method to simulate the distribution of irrigated areas is integrated in the LandSHIFT modelling framework [Alcamo and Schaldach, 2006; Schaldach et al., 2006].

The guiding principle of the LandSHIFT modelling framework is to integrate drivers of land-use change on a country level in order to simulate changes in the spatial distribution of land use on a global five arc minutes grid. Drivers of change include demand and supply side factors, e.g. commodity demands for settlement area, food crops, livestock, timber or energy crops, as well as changes in climate, freshwater availability or agricultural management and technology. Land-use/-cover types comprise a set of major crop types (irrigated and rain-fed), grazing land, urban land and a set of "natural" land cover types such as forests, shrub lands or deserts. We assume that each grid cell is occupied by one dominant land-use type – which on the one hand leads to more artificial spatial patterns, but on the other hand is more transparent and efficient with respect to computation and representation of land-use changes. Exceptions from this concept are made for irrigated and settlement areas which are represented by their fraction per grid cell. The starting conditions are based on the IGBP land-cover classification [Loveland et al., 2000]. Information on the spatial distribution of crop types is generated by a procedure that merges land cover data with sub-national census data [Heistermann et al., submitted]. Appendix B1 documents the development of a map of rainfed and irrigated crop areas.

Each commodity is linked to a particular land-use type, i.e. it can be produced only on cells with this land-use type. Production is allocated to the most suitable cells by changing the land-use type of as many cells as needed to meet the country level demand. For this purpose, each cell contains a vector of production functions for any commodity. Currently, the model contains three sector-specific sub-modules for settlement, crop production, and grazing. Competition for land resources between these sectors is modelled by assigning a priority value to each sub-module that reflects assumptions on its economic importance.

5.2.2 Modelling changes in irrigated areas

The goal of our model of irrigated areas is to allocate a specified expansion of irrigated land within a country to its most suitable location within that country - based on preferences and constraints described in the following paragraphs. The expansion of irrigated land is exogenously specified based on commodity modelling or other methods. Our objective is *not* to simulate the general trends in irrigation expansion, but to simulate the spatial distribution of irrigated areas as a result of various drivers (see 5.2.2.2). These drivers include – in addition to the specified expansion of irrigated area per country – the demand for crop commodities per country and changes in crop yields through technological progress.

The simulation of irrigated areas is embedded in the crop production module and includes the following steps: preference ranking (5.2.2.1); allocation (5.2.2.2); update of river basin consumption-to-availability ratios (5.2.2.3). In every time step, the *preference ranking* first quantifies the *preference* value of each grid cell for a particular irrigated crop and then *ranks* the grid cells of each country according to their preference values. Subsequently, the highest ranking grid cells are allocated to the particular crops until the demand for each crop commodity in each country is fulfilled: first, we allocate irrigated crops until *either* the commodity demand *or* the exogenously specified irrigation expansion is met. The remaining demand is allocated to rain-fed crops.[b] Finally, the irrigation water consumption is updated for each river basin based on the changes in irrigated areas. We will now go through the modelling procedures in detail and describe the set-up for our simulation experiment. Figure 5.2 provides an overview of the modelling procedure while table 5.1 lists all the relevant data used for this study, categorised according to spatial scale and purpose.

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[b] Schaldach et al. [2006] and Alcamo and Schaldach [2006] present the preference ranking method for *rain-fed crops*: it differs *only* in the selection of suitability and constraint factors (the preference ranking for irrigated crops includes *additional* factors) and the related value functions.

Table 5.1: Data requirements for this simulation experiment; see text for further details; every data set which was prepared in the course of this study is documented in the text; see references for details of the other data.

Spatial level	Temporal coverage	Purpose	Attributes	Comment	Source
Country	1993-1997	Baseline definition	Crop production	Production of 17 major crop types per country, from FAOSTAT; see Heistermann et al. (submitted) for categories	FAO, 2006
			Total irrigated area per crop	Specified the area irrigated for each of the above crops; sums up to FAOSTAT total irrigated area per country	prepared for this study
	2020 and 2050	Exogenous drivers	Change in crop production	Change in crop production relative to baseline; based on IMPACT model (Rosegrant et al., 2002); we assume that demand and supply are in equilibrium at every time step	Ringler (pers. comm.)
			Change in crop yields	analogue for crop production, also based on IMPACT	
			Change in population	change in human population count per country relative to baseline	
			Change in irrigated area	Second order scenario: specifies changes in irrigated area per country and crop relative to baseline	prepared for this study
River basin	1961-90 climate normal	Constraint factor	Water availability	Amount of annual renewable freshwater available per river basin without human withdrawals; calculated by the WaterGAP model (Alcamo et al., 2003)	Floerke (pers. comm.)
	1995		Water consumption	Total water consumed per river basin; calculated by WaterGAP	
			Irrigation water requirements	Basin-wide average consumption of water per unit irrigated area; calculated by WaterGAP	
Grid, 5 arc min.	1995	Initial condition	Land use and cover types	Map of 17 major crop types plus grazing land plus a selection of natural land cover types	Heistermann et al, subm.
			Irrigated area	Fraction of area equipped for irrigation per grid cell	Siebert & Doell, 2002
			Settlement density	Fraction of urban and built-up land per grid cell as derived from population density and built-up land demand per capita	Schaldach et al. [in prep.]
		Suitability factor	Slope	Median slope within a 5' grid cell derived from GTOPO30; includes seven slope classes (see reference)	IIASA and FAO, 2000
			Soils	Aggregate suitability of soils in terms of texture, drainage, fertility, depth, salinity	
			River network density	Line density of rivers per grid cell and within a specified neighbourhood; based on river network data for Africa (FAO, 2000)	prepared for this study
		Constraint factor	Conservation areas	Areas designated as national or international conservation areas	IUCN, 2004
Grid, 30 arc min.	1990-2000	Suitability factor	Major crop yields	Yield distribution of major crops as influenced by climate, soil and management (fertilisation and irrigation), N input typical for mid 1990ies	Stehfest et al., subm.
		Production function			
	1961-90	Constraint factor	Relative yield gain through irrigation	Indicator for the increase in grain yield which can be attained through irrigation under the assumption that the entire year is used for crop cultivation	prepared for this study

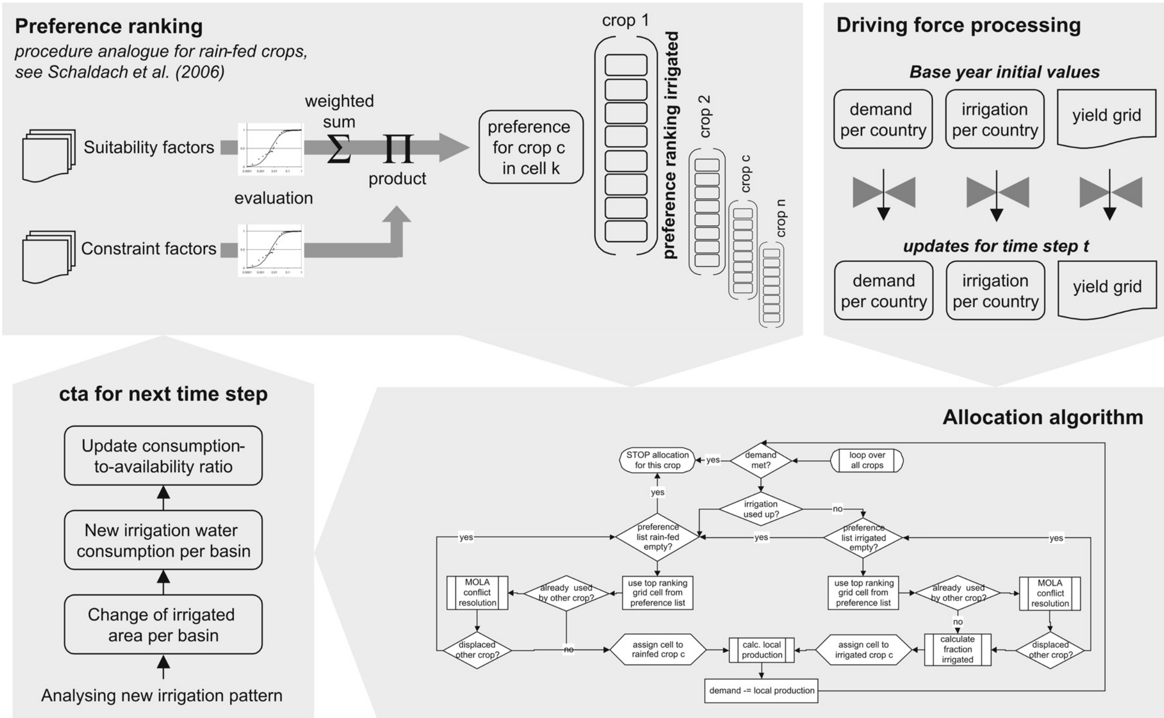

Figure 5.2: Schematic overview of the modelling procedure for a particular time step and country, including the steps preference ranking, driving force processing, allocation, and update of cta (i.e. the ratio between water consumption and water availability in a river basin). See text for further information. Note that the allocation part is also shown in detail in figure 5.5.

5.2.2.1 Preference ranking

A Multi-Criteria-Analysis (MCA) is used to calculate the *preference* value of each grid cell for a particular irrigated crop, based on a set of local cell properties (*factors*). We adapted and modified an MCA-method developed by Eastman et al. [1995]. An MCA-based method is preferable to multiple regression because it is transparent enough to incorporate expert knowledge and flexible enough to incorporate new data layers [Alcamo and Schaldach, 2006].

The MCA-method expresses *preference value* Ψ_k of grid cell *k* as

$$\Psi_k = \underbrace{\sum_{i=1}^{n} w_i f_i(p_{i,k})}_{suitability} \times \underbrace{\prod_{j=1}^{m} g_j(c_{j,k})}_{constraints}, \quad with \sum_i w_i = 1, \; and \; f_i(p_{i,k}), g_j(c_{j,k}) \in [0,1] \qquad Eq.\ 5.1$$

The first term is the sum of weighted factors p_i that contribute to the *suitability* for a particular land-use type. These factors are landscape properties which reflect the "adequacy" of local conditions for irrigation. The factor-weight w_i determines the importance of a single factor p_i in the analysis. The second term of Eq. 5.1 represents land-use *constraints* c_j which are connected by multiplication. These constraints reflect important aspects of human decision making, e.g. policies related to water development or nature conservation. Both p_i and c_j are standardised by *value functions f* and *g* which have a co-domain from 0 to 1 [Geneletti, 2004].

Determining these value functions is a crucial step, because they are expected to be non-linear and scale-dependent [Veldkamp et al., 2001; Verburg et al., 2004]. Therefore, we developed a methodology to assign and parameterise value functions by comparing the spatial distribution of each factor to the current distribution of irrigated areas (*single factor analysis*). Before describing this methodology, we present the choice of suitability and constraint factors. This choice is based on our estimation of the most important factors affecting irrigation potential (see e.g. Fischer et al. [2002]; FAO [1997]; Cassel-Gintz et al. [1997]).

p_1 – terrain slope: This dataset was derived from the GTOPO30 data [USGS, 1998] by IIASA and FAO [2000a] and maps median terrain slopes in seven classes on a five arc minutes resolution. Terrain slopes are considered an important determinant of crop cultivation, particularly under irrigation, because of aspects such as workability, accessibility, and the risk of fertility losses through top soil erosion [Fischer et al., 2002].

p_2 – river network density: We created a line density surface from a dataset of streamlines in Africa [FAO, 2000]. For this purpose, we used the kernel density calculation implemented in ArcGIS Spatial Analyst 9.1 [ESRI, 2005], based on Silverman [1986]. This algorithm spreads out the length of lines in a grid cell over a specified radius. The density is greatest at the line location and diminishes to zero when reaching the radius. For each output cell, the sum of the intersecting spreads is calculated. We use the river network density as a proxy for distance to river and thus for the accessibility of surface water and costs of water transport. This is an important aspect of suitability since surface water bodies are still the source of water for about 80 percent of all irrigated areas in Africa [Frenken, 2005].

p_3 – settlement density: Cultivated areas – be it rain-fed or irrigated – are located in close proximity to settlements which provide infrastructure, market access and/or local demand for crops. Schaldach et al. [2006] derive settlement density from human population density and country specific per capita requirements for built-up land. The LandSHIFT model simulates changes in extent and location of settlements which affects irrigation suitability, but also might imply the conversion of existing (irrigated) cropland to settlement area.

p_4 – potential irrigated crop yield: Potential yields of irrigated crops have been computed on a 30 arc minutes resolution with the DayCent model [Stehfest et al., submitted]. This ecosystem model is the daily version of the CENTURY model [Parton et al., 1988]. It was originally published by Del Grosso et al. [2000] and Parton et al. [1998] and was adapted to simulate water-, temperature- and nitrogen- limited yields of major crops on the global scale [Stehfest et al., submitted]. For the global simulations, climate is specified on a 30 arc minutes grid [New et al., 1999]. Model inputs include country-average N fertilizer application rates. Irrigated yields are simulated by relaxing the water constraints in the model. Note that the resulting spatial yield distributions are also used in the allocation algorithm in order to assign crop specific production functions to each grid cell (see 5.2.2.2).

p_5 – combined soil properties: This data set integrates over different attributes of the FAO soil map of the world (including soil depth, drainage, salt content etc.) and assigns seven classes of suitability. Like the slope data, it was produced by IIASA and FAO [2000b] and documented by Fischer et al. [2002]. Note that we do not directly adopt the suitability values represented by this data set. Instead, we evaluate how these suitability values actually relate to the current distribution of irrigated areas. Based on that, we re-assign suitability values between 0 and 1 (same procedure as for the other suitability and constraint factors, please see page 104 ff.).

c_1 – relative yield gain attained by irrigation: This constraint represents the potential increase in crop yield that could be achieved if cropland is irrigated. It is applied as an indicator to identify locations where irrigation would provide a poor improvement in crop yield and is thus unlikely to be economically efficient. The DayCent model [Stehfest et al., submitted] is also used to calculate this factor: using the parameterisation of a typical, widespread crop (maize), we simulate the potential yield under rain-fed and irrigated conditions, assuming that the maize yield not only accumulates over a single cropping cycle but over the entire year. Doing so, we implicitly account for the fact that irrigation often serves to extend the growing period beyond the rainy season (in order to allow multiple cropping cycles per year). By comparing the resulting yields under rain-fed and irrigated conditions, we finally compute the relative yield gain.

c_2 – water consumption-to-availability ratio: This constraint addresses the availability of water for irrigation on a basin level. It takes into account two factors: the *annually renewable freshwater availability* per basin before any withdrawal (based on precipitation and evapotranspiration), and the *consumption of freshwater* by three different sectors. Both values are computed by the WaterGAP model [Alcamo et al., 2003; Döll et al., 2003; Döll and Siebert, 2002] for the base year 1995 for river basins derived from a 30 arc minutes global drainage direction map [Döll and Lehner, 2002]. The ratio between water consumption and availability (*cta*) is a common indicator of water scarcity [WMO, 1997]. We assume that high values of *cta* will constrain the withdrawal of additional freshwater for irrigation. In resource economics, this is also known as the "stock effect" or the "depletion effect" [ADB, 1997; Sweeney, 1992]. An increase in cta implies an increase in the marginal extraction costs for irrigation water [ADB, 1997; Al-Sheikh, 1998; Feitelson and Fischhendler, 2006; Koundouri and Xepapadeas, 2004], and an increase in the marginal environmental costs of irrigation [Bucknall et al., 2003; CGER, 1996]. Unfortunately, it is not feasible to estimate actual extraction and environmental costs globally on a fine grid basis. Therefore we assume that the potential for irrigation decreases monotonically with increasing cta (see page 105 ff. for the derivation of a functional relationship).

c_3 – nature conservation: assume the availability of two equally suitable grid cells – one protected, one unprotected. It seems obvious that the protected one is less likely to be converted to agriculture than the other. On the other hand, many nature reserves around the globe are actually encroached by agriculture or other human interference [WWF, 2004]. One could think of different ways to quantify how rigorously the nature protection status constrains agricultural encroachment (e.g. by considering country level governance indicators such as published by Kaufmann et al. [2005]).

So how can appropriate value functions *f(p)* and *g(c)* be derived which normalise the factor domain and account for potential non-linearities? Simply transferring expert knowledge or rules from small scale land evaluation to large spatial scales could lead to scaling and compatibility problems due to the coarse representation of suitability factors [Veldkamp et al., 2001]. As one example: in the "real world", there *might* be a maximum terrain slope that is prohibitive to crop cultivation. But this threshold will not be meaningful on a five arc minutes grid because the actual slope is smoothed so much that it is highly uncertain how much of the grid cell has a slope above this threshold and how much below. Another instructive example is that about 35 percent of the irrigated areas in Africa are located on grid cells classified as entirely unsuitable with respect to soil properties (according to a comparison of data bases from IIASA and FAO [2000b] and Siebert et al. [2002]). Although this might be *partly* due to uncertainty effects of both data sets, the scaling problem has to be addressed. One option would be to perform a multiple regression analysis in order to quantify the impact of every factor [see e.g. Lambin et al., 2000; Verburg et al., 2002]. In this study, we take an alternative approach and first evaluate every single factor through a value function and then combine these value functions to an aggregate preference value (Eq. 5.1). This facilitates *i)* the consideration of non-linearities; *ii)* the consideration of expert knowledge and scenario assumptions, e.g. assumptions about the enforcement of nature conservation; *iii)* the inclusion of additional information layers. In this study, we use the *spatial distribution of irrigated areas* as published by Siebert et al. [2002] in order to evaluate our suitability and constraint factors. We now describe the general methodology to derive the value functions (see also figure 5.3). Afterwards, exceptions are discussed for the factors c_2 and p_4.

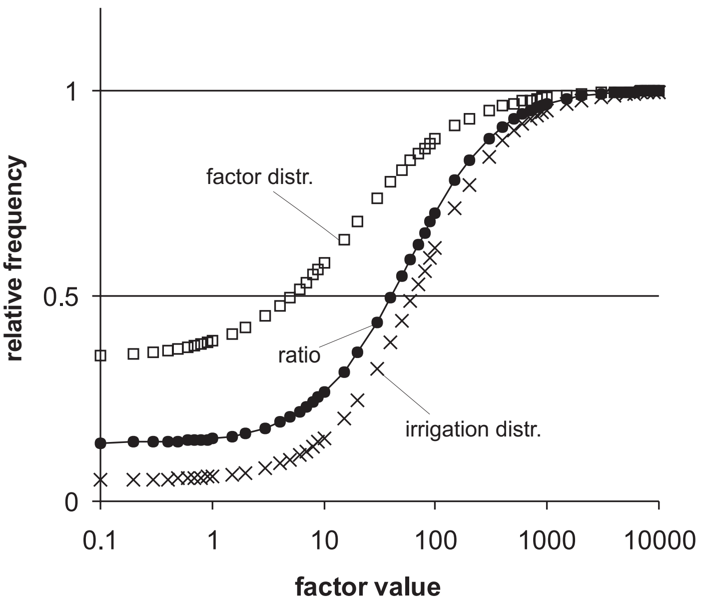

Figure 5.3: Exemplary derivation of a value function as applied for the suitability and constraint factors (exceptions: p_4 and c_2). Hollow squares: cumulative frequency distribution of the factor over the study area; crosses: cumulative frequency distribution of irrigated area over the factor in the study area; black circles: ratio between irrigation distribution and factor distribution. The ratio curve can directly by interpreted as a value curve. It might occur that the irrigation distribution and factor distribution intersect, leading to ratio values larger than 1. In this special case, the ratio curve simply has to be normalised to a maximum value of 1. *Note: discrete class ranges are indicated by horizontal distance between data points*.

Deriving the value functions (*single factor analysis*)

We assume the value functions to be either monotonically increasing (p_2-p_5, c_1) or decreasing (p_1, c_2, c_3). First, we divide the factor domain into class ranges. By comparing the map of a particular factor and the map of irrigated areas, we compute the percentage of the total irrigated area that falls into a certain value class of this factor. From that, we construct a cumulative frequency curve. Assuming a monotonic relationship, this curve indicates the factor range over which the irrigated area significantly increases. This might already be interpreted as an increase in suitability. But if a large fraction of the study area falls into the factor *class i*, it is more likely that this class also contains comparably large shares of the total irrigated area. Let's presume that there is absolutely no influence of a particular factor on the distribution of irrigated areas and that the irrigated area would be randomly distributed over the study area. Then the share of irrigated area falling into factor class i would only depend on the relative frequency of factor class i. Thus, we need to know how the distribution of irrigated areas over the suitability factor classes deviates from the frequency distribution of the factor itself. For this purpose, we construct the cumulative distribution curves for both the factor itself and the distribution of irrigated areas over the factor. The deviation can be measured as the *ratio* between the "irrigation curve" and the "factor curve". A constant ratio (being equal to 1) over the whole factor domain would indicate that the irrigated area would be randomly distributed over the study area and that there would be no relation between factor and suitability. Accordingly, an increase in the *ratio* indicates an increase in suitability. Furthermore, the difference between the minimum and maximum value of the ratio curve also provides a good indicator for the "strength" of the relationship. Interpreting the "ratio-curve" as a value curve, we use an ordinary least-squares method to fit an appropriate continuous function *f(p)* - or *g(c)*, respectively (Eq. 5.2).

$$f(p), g(c) = \alpha_1 + \frac{\alpha_2}{1 + \alpha_3 \cdot \exp[-\alpha_4 \cdot \log(p)]} \quad \textit{with } \alpha_{1-4} : \textit{shape parameters} \qquad \textit{Eq. 5.2}$$

As already pointed out, exceptions from this procedure had to be made for two factors: the constraint factor c_2 (consumption to availability ratio) and the suitability factor p_4 (potential irrigated yields). The derivation of value functions for these two factors is described in the following.

Exception 1: *Consumption-to-availability ratio (cta)*

How does water scarcity (expressed as cta) constrain the expansion of irrigation in a river basin? As already pointed out, we assume that any increase in cta *potentially* constrains the utilisation of additional freshwater. In order to quantify this relationship in a value function, we have to modify the above method. This is simply due to the fact that cta is highly dependent on the distribution of irrigated areas – because the calculation of basin level irrigation water consumption in the WaterGAP model is based on the spatial distribution of irrigated areas (see Döll and Siebert [2002] for details). The application of the above method only makes sense when the factor distribution is independent from the distribution of irrigated areas. Thus, we have to use an alternative approach.

In figure 5.4a, the bars represent the fraction of total irrigated area that falls in river basins of a specific cta-class (class width: 5 %). The largest share of irrigated areas is found in basins with low cta values and obviously, the occurrence of irrigated areas decreases with increasing cta. Can we explain this finding with the constraining effect of water scarcity? Consider the two curves in figure 5.4a: one shows the average annually renewable water availability in those basins that fall into a specific cta-class, the other shows the average annual irrigation water requirements per unit irrigated area. We see that the irrigation water requirements increase with increasing cta, while water availability decreases. Both increasing irrigation water requirements and decreasing water availability represent increasingly arid conditions. Accordingly, increasing irrigation water requirements also indicate a stronger incentive to prefer irrigated over rain-fed cultivation.[c] Why does the occurrence of irrigated areas decrease in spite of an increasing incentive to irrigate? We explain this fact by the constraining effect of water scarcity (as expressed by cta). High cta values imply that the availability of water resources, be it groundwater or surface water, is significantly limiting further irrigation expansion.

[c] Note that the irrigation water requirements for lowest cta class are at around 200 mm/a. Although this value is low as compared to values in higher cta classes, it proves that rain-fed crop cultivation would already be considerably water deficient in those basins with a cta < 5 %.

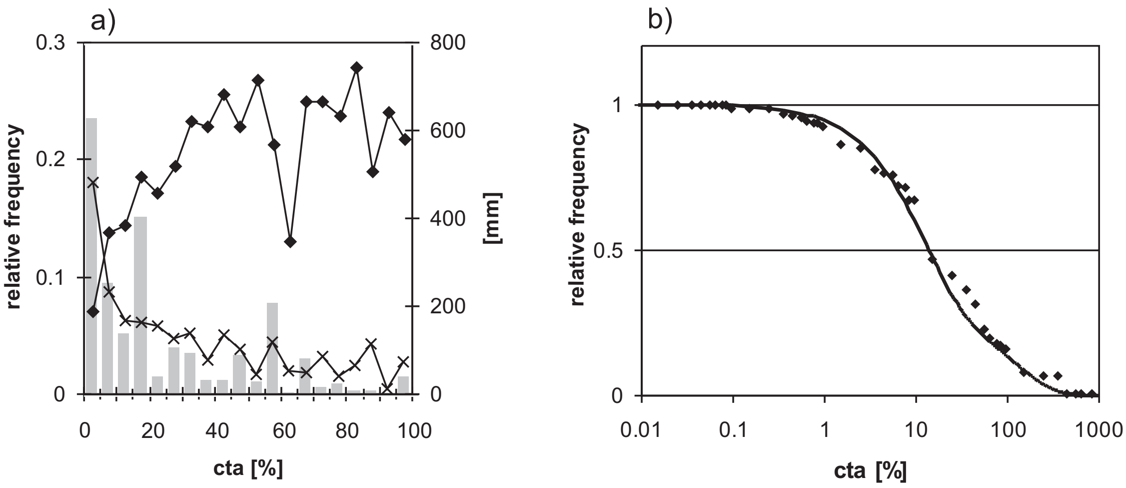

Figure 5.4: Relationship between water scarcity (expressed as consumption-to-availability ratio) and the distribution of irrigated areas (see text for interpretation). **a)** grey bars: fraction of total irrigated area in basins within corresp. cta class; black rhombi: average irrigation water requirements per unit irrigated area [mm] in basins within corresp. cta class; black crosses: average annually renewable freshwater availability [mm] in basins within corresp. cta class. Only shows the range of cta < 100 % **b)** cumulative frequency distribution of irrigated areas over cta. Note that about 15 % of all irrigated areas are located in basins with a cta higher than 100 %. Consider also that for both figures (a and b), we analysed the *global* distribution of irrigated areas in order to account for a wider spectrum of conditions. To get robust results, we excluded basins smaller than 10,000 km^2 and with a water availability smaller than 5mm per year.

How can we operationalise this finding by defining a value function for cta? The co-domain of the value function should be between zero and one and it should not be sensitive to the definition of cta class widths. The value function should be monotonically decreasing with cta and it should account for the fact that small increases in cta already can constrain irrigated cultivation. At the same time, it should consider that cta values higher than 100 % are not necessarily prohibitive to irrigation. In some regions, water is consumed unsustainably, particularly from groundwater resources, which leads to falling groundwater tables [Cosgrove and Rijsberman, 2000; Vörösmarty et al., 2005]. All these demands on the value function are met if we use the cumulative frequency distribution of irrigated areas over cta as shown in figure 5.4b. It covers the entire domain of possible cta values (also cta > 100 %), but at the same time, it captures the strong increase in water limitation in the cta range below 100 %.[d] Consider some characteristic curve points: the constraint value at a cta of 100 % is 0.13, meaning that the suitability of a grid cell would be considerably reduced (by over 85 %). At a cta between 10 and 20 %, suitability would be reduced by around 50 %. Interestingly, this coincides with the cta-range generally regarded as an indicator of moderate to high water stress [WMO, 1997]. Interpreting the cumulative curve as a value function, we can fit a function (Eq. 5.3) in order to generate a continuous distribution.

$$g(c_2) = \alpha_1 \cdot e^{-\beta_1 \cdot c_2} + \alpha_2 \cdot \exp^{-\beta_2 \cdot c_2}, \; \alpha_1 + \alpha_2 = 1, \; \beta_{1-2} : shape\ parameters \qquad Eq.\ 5.3$$

[d] Note that cta is a ratio of two quantities. Therefore it is highly susceptible to uncertainties and errors, particularly in small basins with a very low water availability – which could also cause unrealistically high cta values. We already account for this effect by entirely excluding water basins with a water availability below 5mm per year (as e.g. in central Sahara) from this analysis (based on the fact that more than 95 percent of all irrigated areas are located in basins with a water availability higher than 5mm per year).

Obviously, this procedure is very approximate and an abstraction of practical irrigation management. Besides, it smooths over various climatic and socio-economic conditions. Nonetheless, it provides a rough indication of how irrigation is constrained at different stages of water scarcity.

Exception 2: *Crop yields*

The map of current irrigated areas that we employ to calibrate and validate our suitability analysis is not crop specific (see section 5.2.3). Hence, we cannot use it to derive value functions for the individual crop yields. Instead, we use a very simple approach to evaluate the contribution of irrigated crop yield to suitability (this is the same approach as for rain-fed crops [see Schaldach et al., 2006]. The crop yield is normalised between zero and one by using the minimum (*min*) and maximum (*max*) yield of the respective crop *c* within the simulated country according to Eq. 5.4.

$$f_c(p_4) = \frac{p_4 - \min_c}{\max_c - \min_c} \qquad \textit{Eq. 5.4}$$

Consequently, every country has a set of value functions for every crop which is also necessary because the simulated yield levels differ substantially between countries because of country specific nitrogen application rates [Stehfest et al., submitted].

5.2.2.2 Land allocation

The allocation algorithm of the crop production module considers both rain-fed and irrigated crops. Figure 5.5 provides an overview of the procedure: the demand for crop commodities is satisfied for every single country by allocating grid cells according to a preference ranking for each crop (5.2.2.1). Each grid cell has assigned a vector of production functions that quantifies the potential *local* production per year for each crop (see below, Eq. 6). In case a grid cell is allocated to a particular crop type, the local production on this grid cell contributes to fulfil the country level demand for this crop. First, we allocate cells to *irrigated* crops until the exogenously specified amount of irrigated area is met (see section 5.2.2). We refer to this amount as the "maximum allowable irrigated area per country". The remaining demand is satisfied by *rain-fed* crops according to the rain-fed preference ranking [Alcamo and Schaldach, 2006; Schaldach et al., 2006]. Note that the "maximum allowable irrigated area per country" might not be entirely used if the demand is fulfilled before the allowed irrigation expansion took place (i.e. demand is the dominant driver).

The allocation procedure is organised as an iterative loop which handles the competition between crop types as a "compromise solution"-problem. For this purpose, a modified MOLA (Multi Objective Land Allocation) heuristic for the spatial allocation is implemented [Eastman et al., 1995]. The MOLA algorithm is modified so that conflicts are resolved not only by preferring the land-use type with the highest preference value but also by seeking pattern stability. In other words, if there was no change in drivers (i.e. no change in maximum allowable irrigated area, crop demands and crop yields), no change in land-use patterns would occur, either. In this way we account for the fact that our knowledge of suitability and constraint factors and their interplay is incomplete and uncertain.

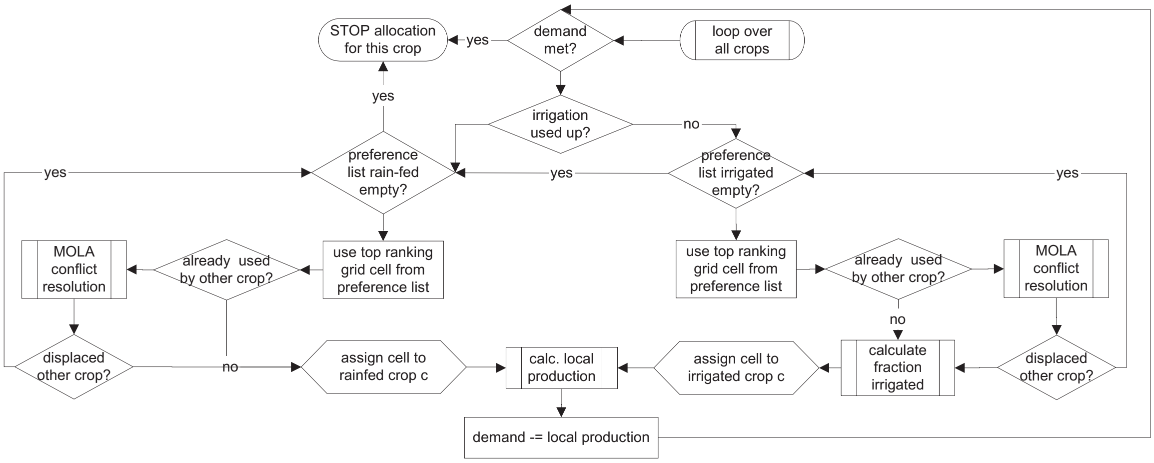

Figure 5.5: Schematic overview of the allocation algorithm in the LandSHIFT crop production module.

The production function *P* of a grid cell *k* for a specific crop *c* at time *t* is determined by the potential irrigated and rain-fed crop yield (Y_{IR} and $Y_{RF,}$ as calculated by the DayCent model), the cell area *A*, the fraction of settlement *s*, the fraction of irrigated area *f*, and a technological improvement factor τ (exogenous scenario assumption):

$$P_{c,k,t} = \gamma_c \times \tau_{c,t} \times (1 - s_{k,t}) \times A_k \times \left[\left(1 - f_{k,t}\right) \times Y_{RF,c,k} + f_{k,t} \times Y_{IR,c,k} \right] \qquad \textit{Eq. 5.6}$$

The factor γ is a correction factor which accounts for the deviation between country level crop production as reported by FAO and country level crop production as calculated by combining our yield maps with our initial crop distribution map. Such a factor is necessary to make up for a broad range of uncertainties, particularly in the representation of management (multi-cropping, crop rotations, nutrient inputs other than nitrogen etc.), but also for model errors, location errors in the crop map and errors in FAO country statistics of yields, irrigation and crop production.

As already discussed, the irrigated area per grid cell is represented as a fraction (the remaining fraction of cropland in that grid cell is rain-fed). If a particular grid cell is allocated to irrigated cropland, we first assign the fraction of irrigated area from the *previous* time step. The *additional* increment of irrigated area assigned to that grid cell depends on *the previous land-use* and on *the cell's preference value* for the particular irrigated crop (see 5.2.2.1). If the cell was previously occupied by cropland, we assume that the additional increment equals the preference value. If the cell was previously no cropland, we assume the entire cell to become irrigated. This is due to our concept of dominant land-use types (see 5.2.1): if we incrementally increased irrigation on a previously natural cell, we would necessarily have to assign rain-fed production to the rest of the cell – even if it was entirely unsuitable for rain-fed production.

5.2.2.3 Update consumption-to-availability ratio

For each time step *t+1*, the consumption-to-availability ratio in all river basins is updated based on the changes of irrigated area in the previous time step *t*. Based on the increase of irrigated area A_{IR} in a basin, we compute the additional irrigation water consumption ΔC_{IR}. For this purpose, we use the water requirements *REQ* per unit irrigated area in a particular basin, as provided by the WaterGAP model (see Döll and Siebert [2002] for details about the computation of irrigation water requirements). From the additional irrigation water consumption, we derive the increase in *cta* (by relating ΔC_{IR} to freshwater availability *AVL*).

$$\Delta C_{IR,t+1} = \left(A_{IR,t+1} - A_{IR,t}\right) \cdot REQ \quad \Rightarrow \quad \Delta cta_{t+1} = \frac{\Delta C_{IR,t+1}}{AVL} \qquad \textit{Eq. 5.7}$$

5.2.3 Calibration and validation

The main caveat for validating our modelling approach is the lack of appropriate data. At least, we would need two large scale maps of irrigation distribution at two adequately distant points in time: one to calibrate the value functions, and the second to compare our simulated changes against actual changes. Yet, there are only two large scale maps of irrigated area available which are *both* representative for the mid to end 1990ies [Siebert et al., 2002; Thenkabail et al., 2005]. As we can only use *one* map for *one* point in time, we decided to use the more established product published by Siebert et al. [2002]. We used part of this data set to calibrate the model and part to validate it. The main strategy was to confirm the validity of our preference ranking - a common procedure in land-use change modelling [Pontius and Schneider, 2001], since the spatial dynamics are governed by the preference ranking. For this purpose, we divided the set of African countries into two sub-sets: one sub-set was used to calibrate the value functions for the suitability and constraint factors, based on the spatial distribution of irrigated areas. The other sub-set was used to evaluate the resulting preference maps – simply by interpreting the pattern of *current irrigated areas* as a pattern of *changes in irrigated areas* (as compared to a “virtual initial condition” with no irrigation at all).[e] To evaluate the validity of the preference maps, we applied the *relative operating characteristic* (*ROC*) method, a well established statistical method which was adopted by Pontius and Schneider [2001] for the validation of suitability maps in land-use change modelling. The *ROC* is a summary statistic derived from several two-by-two contingency tables, where each contingency table corresponds to a different simulated scenario of land-use change. The categories in each contingency table are *actual change* and *actual non-change* versus *simulated change* and *simulated non-change* (refer to Pontius and Schneider [2001] for a detailed description). The *ROC* measure has a co-domain between zero and one, where any value above 0.5 indicates that the model performs significantly better than a random allocation of land-use. A value of 1 indicates perfect agreement. To derive the *ROC* for a sub-set of countries, we first calculated the *ROC* value for every single country and then used the irrigated area per country as a weight to calculate the

[e] The split of African countries into calibration and validation sub-sets is documented in Appendix B2. The split was generated by dividing the continent into six regions based on the GEO classification (UNEP, 2002) and arbitrarily selecting two or three countries from one region into the calibration sub-set (but always less or equal than half of the countries within a region).

average *ROC* of all countries in the sub-set. Based on these procedures, calibration and validation were carried out according to the following steps:

1. First, the value functions were quantified by using the above method and only considering the calibration sub-set of countries. The corresponding curves are shown in figure 5.6. Note that we ignored the suitability factor p_4 (irrigated yields) in the calibration/validation exercise because the reference data set of irrigated areas is not crop specific.

2. Then, the factor weights were derived: the more a single suitability factor contributes to the explanation of the current irrigated area pattern, the higher should be its weight. Hence, the value ROC_i was calculated for every single suitability factor i, using only the calibration sub-set of countries. The factor weights w_i where then computed as

$$w_i = \frac{ROC_i}{\sum_i ROC_i} \qquad \textit{Eq. 5.8}$$

3. Based on steps 1 and 2, we first created a suitability map (which *only* considers the suitability factors, but ignores the constraints). The resulting ROC for the validation sub-set of countries was 0.79 which indicates a very good agreement between suitability pattern and irrigation pattern.

4. Subsequently, we computed the *ROC* for the preference map by also considering the constraint factors, resulting into an ROC of 0.67 for the validation sub-set**.** The decrease in the ROC value is a logic consequence of the fact that those basins with the highest amount of irrigated areas might already undergo severe water stress - which leads to a strong reduction of the preference value according to figure 5.4. The important point is that the second ROC is still significantly higher than 0.5. This illustrates the efficient interplay between the constraint factors c_1 and c_2: the first "promotes" irrigation in water scarce regions, the second limits additional irrigation. The reduction in ROC from 0.79 to 0.67 indicates that the irrigation potential for intensively irrigated basins is already being constrained by high cta values (i.e. water scarcity). At the same time, these basins still carry further potential as is indicated by the ROC > 0.5.

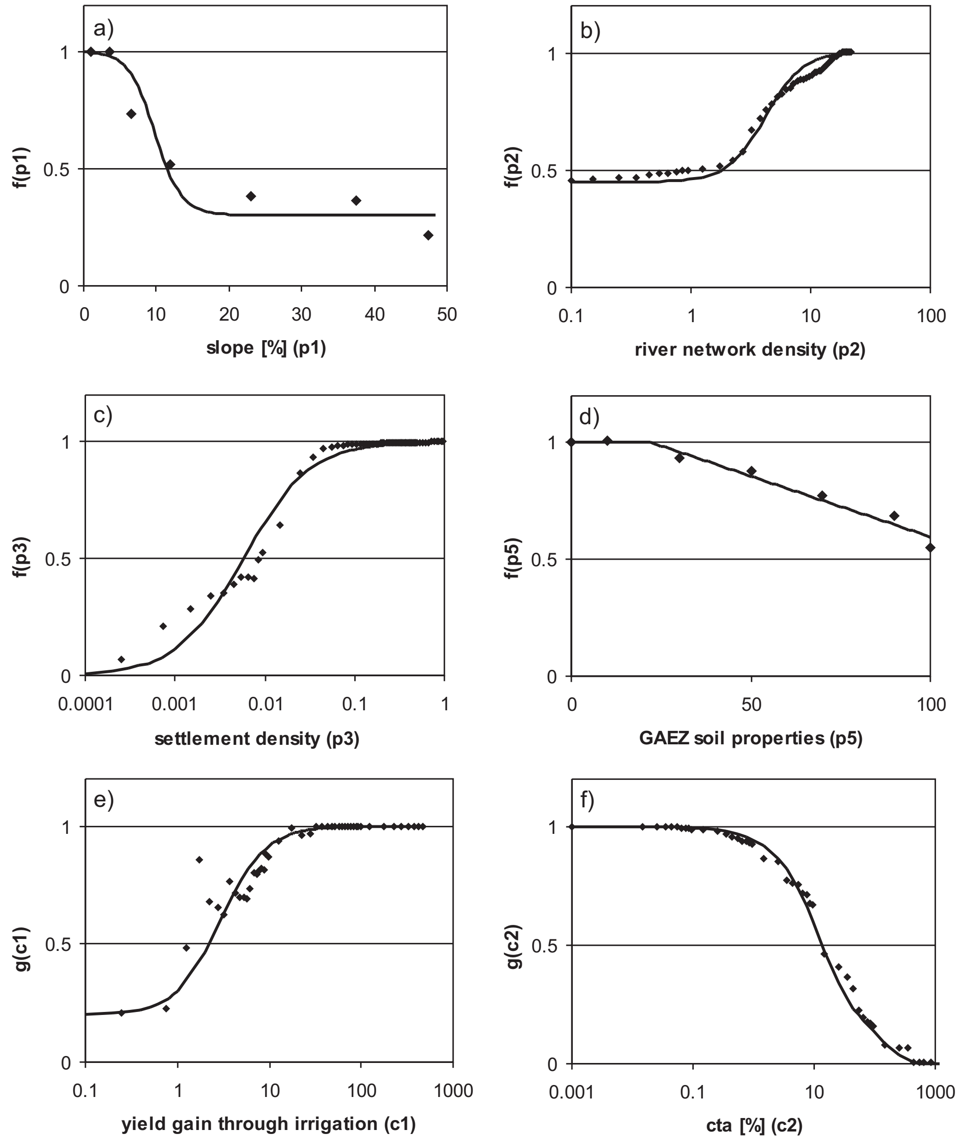

Figure 5.6: Overview of value functions for all suitability and constraint factors. The value functions give an impression of the non-linear relationship between a factor and its contribution to the preference for irrigation. The rhombic dots represent the “ratio curves” as discussed in section 5.2.2.1 and shown in figure 5.3, while the black line represents the fitted function according to Eq. 5.2 (except for Fig. 5.6d, where we used a simple ramp function).

5.2.4 Set-up for simulation experiment

To demonstrate a potential application of the presented methodology, we carry out a simulation experiment in which we simulate the distribution of irrigated areas in Africa until the year 2050. As a reference scenario, we choose the scenario *Order from Strength* from the Millennium Ecosystem Assessment [MEA, 2005]. *Order from Strength* represents a regionalized world with an emphasis on security and economic growth, implying low response capacities to ecosystem problems in many parts of the world [Carpenter et al., 2005]. The scenario assumes a population growth in

Africa from about 800 million people in 2000 to more than 1.9 billion in 2050 which (together with economic growth) leads to a large increase in food demand. Crop demand changes as well as yield changes driven by technological improvements have been quantified by the IMPACT model [Rosegrant et al., 2002b] for major economic regions which we have mapped to the country level. This mapping, as well as the demand and yield changes, are documented in appendix B4. Appendix B3 relates the crop commodities used in the IMPACT model to the crop commodities employed in LandSHIFT and DayCent.

Based on this reference scenario, we analyse different variants.[f] In this case, the variants explore the following aspects (see table 5.2 for an overview):

- *effect of different general trends of irrigation expansion* (i.e. changes in the "maximum allowable irrigated area per country"): the scenario family *S40* assumes a *moderate* expansion of irrigated areas until 2050 (40 % increase compared to 1995, based on FAO projections [FAO, 2002]). Another scenario *S60* assumes *higher* changes (60 % increase).
- *effect of feedback*: within the *S40* family, we analyse how the cta-feedback affects the spatial pattern of irrigation expansion. In the scenario *S40a*, cta is updated every time step (i.e. every five years), while in scenario *S40b*, the cta remains at its initial level, ignoring the changes in irrigated areas.
- *effect of different value functions for cta*: also within the *S40* family, we investigate the sensitivity of results to the value function $g(c_2)$ for cta (see page 105 ff.). In scenario *S40a*, we apply the original function as shown in figure 5.4. In scenario *S40c*, we assume that river basins with a cta larger than 100 % are fully excluded from any further expansion of irrigated area (i.e. we modify Eq. 5.4 so that $g(c_2) = 0$ *if* $c_2 > 100$ %).

Table 5.2: Overview of scenario set-up to be analysed in the simulation experiment

Scenario level	**Assumption**	**Scenario S40a**	**Scenario S40b**	**Scenario S40c**	**Scenario S60**
Reference scenario	changes in food demand [%]	*according to MA Order from Strength, quantified by IMPACT model (see Appendix D)*			
	improvement of yields [%]				
Variants	change of maximum allowable irrigated area per country [%]	+ 40 % in 2050	+ 40 % in 2050	+ 40 % in 2050	+ 60 % in 2050
	feedback	yes	yes	no	yes
	cta value function	as in Fig. 5.4	as in Fig. 5.4, but no additional irrigation if cta > 100	as in Fig. 5.4	as in Fig. 5.4

[f] Under the term *variant* we subsume assumptions which are not included by the published reference scenario. This might include the specification of additional exogenous drivers or assumptions on model parameters for the purpose of sensitivity analysis.

Please note that in order to focus on the new irrigation model, other aspects of future irrigation development are held constant in this simulation experiment.[g] For the same reason, we ignore the role of nature protection - simply by assuming that the value function for constraint factor c_3 (conservation constraint) has a constant value of 1 even for protected areas (see also page 103).

5.3 Results and Discussion

In this chapter, we present results from our simulation experiment. First, we illustrate the impact of the different scenarios on the spatial distribution of irrigated areas and cta. In addition, we analyse how suitability is constrained by cta under different scenarios and at different points in time. Finally, we discuss important sources of conceptual and data related uncertainty.

5.3.1 Changes in the spatial distribution of irrigated areas and cta

To begin with, we provide a regional example to illustrate the grid-based changes in irrigated areas for the scenarios S40a, S60 and S40b (figure 5.7). We chose the example of Northern Africa as an important region for irrigated areas. Subsequently, we use the grid-based pattern of changes to compute the changes in irrigated area on a river basin level from 2000 to 2050 and the resulting change in the cta-ratios. Figure 5.8 shows the resulting patterns for the scenarios S40a, S60 and S40b. Additionally, we show the differences in cta changes for S40a, S40b and S40c in figure 5.9.

As a direct consequence of distinct preference patterns, we can see very heterogeneous patterns of change within countries. If a basin has a large pool of *suitable* grid cells, it will attract much of the additional irrigated area until the effect of cta becomes prohibitive to further irrigation expansion. If this constraining effect is missing, these basins attract more and more irrigation regardless of their water availability. This becomes apparent by comparing figure 5.8a and c (and figure 5.9a): in scenario S40b, additional irrigation is unrealistically attracted to only a few basins which actually become concentrated with irrigation. For example in Egypt, much of the additional irrigated area is allocated to the coastal regions because the Nile basin is already heavily constrained by cta in the base year 2000. However, in S40a, the water resources of these coastal regions are quickly exhausted so that subsequently, irrigation is expanded in the Nile basin again. In S40b, this effect is completely ignored because the coastal basins are exploited regardless of the depletion of their water resources.

[g] First, we constantly assume current climate conditions (1961-90 climate normal). Second, we assume that irrigation efficiency is constant (which would affect the crop water requirements per unit area as calculated by WaterGAP). Third, we assume that water consumption does not change except in the irrigation sector (meaning water consumption is kept constant in households, industry and livestock production). Finally, we only simulate changes in the crop sector and “switch off” the remaining LandSHIFT sub-modules. This implies that the settlement distribution will be constant and changes in grazing land will only occur as a result of cropland expansion.

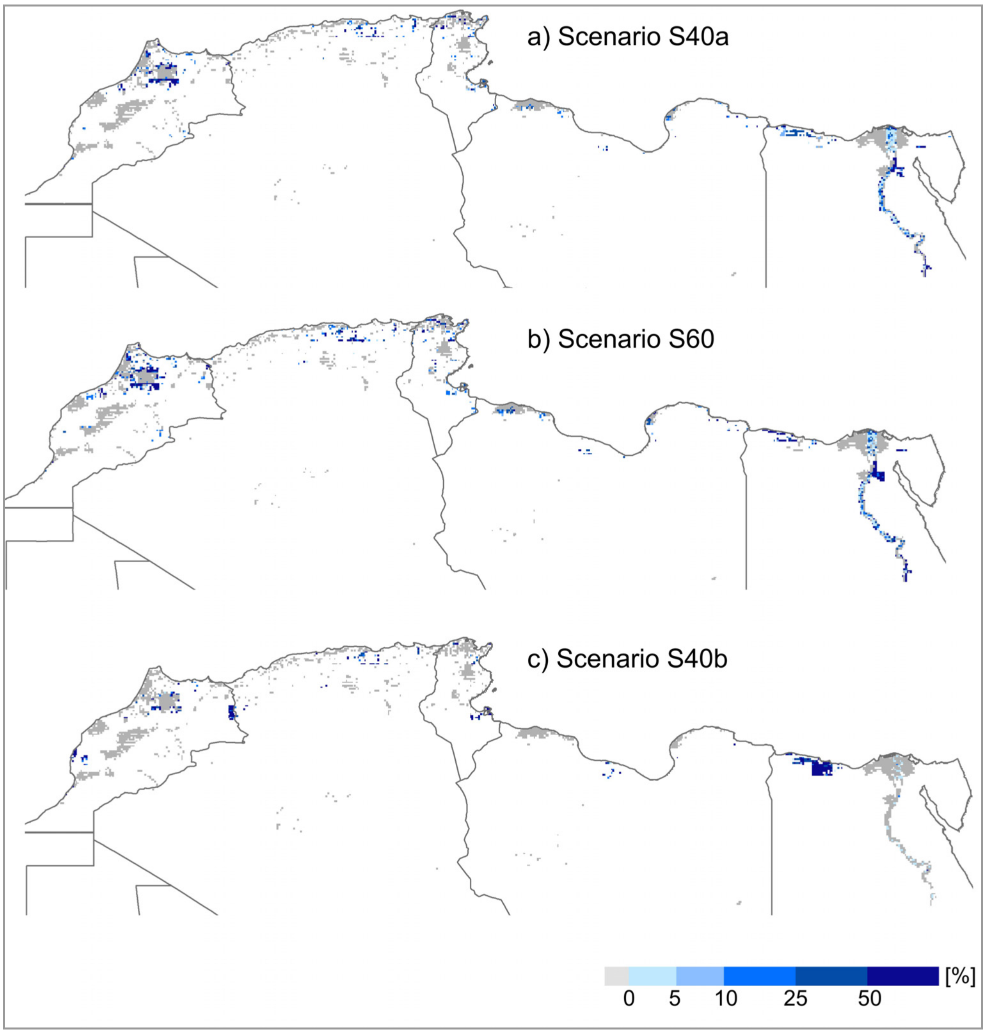

Figure 5.7: Changes in irrigated areas on a 5 minutes grid resolution in 2050 compared to 2000. The section shows Northern Africa (where irrigation is most frequent), representing the scenarios S40a, S60 and S40b. The blue scale indicates changes as incremental percent change per grid cell while the dark grey shade indicates the reference distribution in the year 2000.

Figure 5.9 highlights the effects of cta-feedback and a modified value function for cta. It shows the differences in cta change between S40a and S40b (figure 5.9a) and between S40a and S40c (figure 5.9b). We again see the significant effect of feedback on the resulting cta distribution (figure 5.9a). From figure 5.9b, we infer that a modified cta value function hardly affects the model results. This implies that the model is quite robust to the formulation of the constraint value function $g(c_2)$: it only makes a slight difference whether the value function becomes zero for cta values larger than 100 % or whether it follows the curve progression shown in figure 5.4b. In most of the basins, the original formulation of $g(c_2)$ in S40a already excludes most of the basins with cta-ratios larger 100 % from further irrigation expansion.

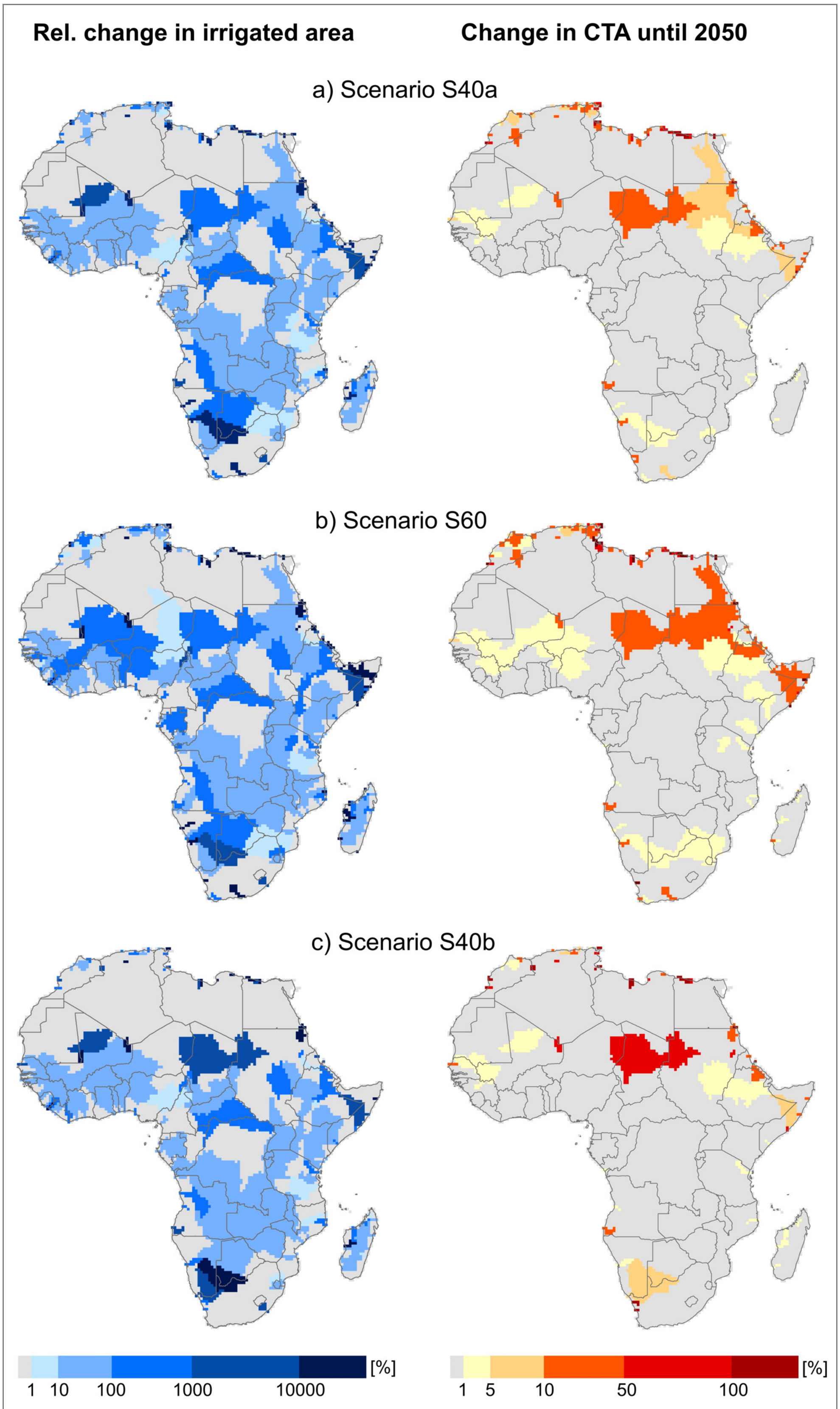

Figure 5.8: Basin level changes in irrigated areas and consumption-to-availability ratio (cta) for the scenarios S40a, S60 and S40b. The left hand side shows relative changes in irrigated area per basin in 2050 as compared to the year 2000. The right hand side shows the resulting cta changes from 2000 to 2050, represented as the *difference* between 2050 and 2000 ($\Delta cta = cta_{2050} - cta_{2000} = (\Delta consumption)/availability$).

Comparing scenarios S40a and S60 in figure 5.8, we see that the higher increase in total irrigated areas in S60 leads to the development of water resources in basins still undeveloped in S40a. Nonetheless, the major share of the additional irrigated areas rather aggravates water scarcity in those basins already affected in scenario S40a.

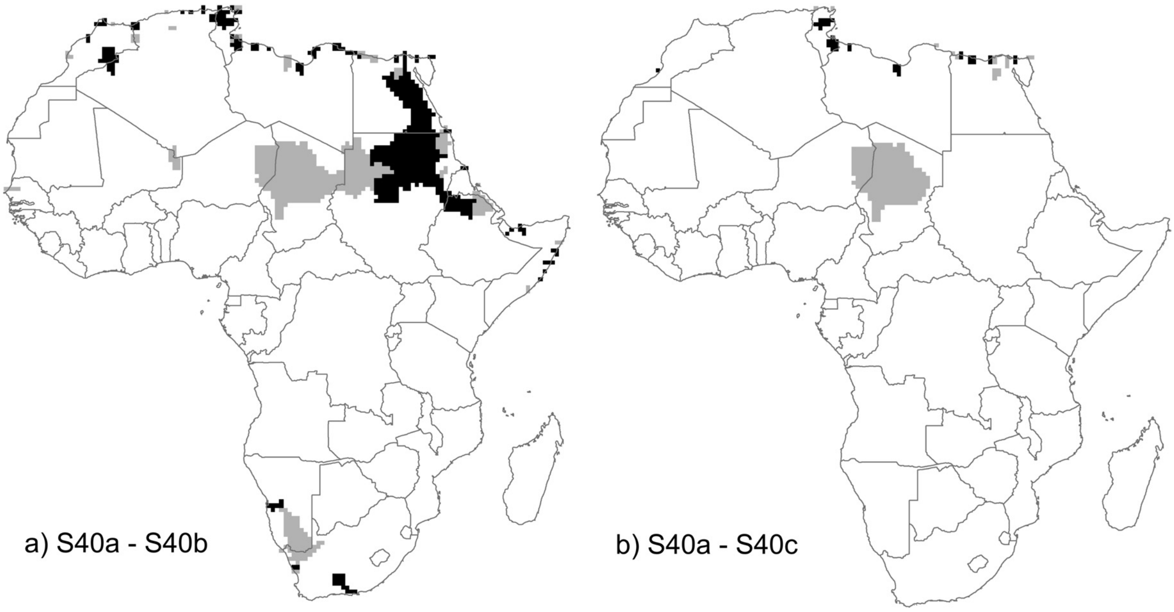

Figure 5.9: This figure compares the resulting change in cta as shown in Fig. 8 for the scenarios $S40_a$, $S40_b$, and $S40_c$ by a) subtracting the cta changes in $S40_b$ from the changes calculated in $S40_a$, b) subtracting the cta changes in $S40_c$ from the changes calculated in $S40_a$. Black colour indicates areas where $\Delta cta(S40_a)$ - $\Delta cta(S40_{b,c}) > 5\%$, grey colour indicates areas where $\Delta cta(S40_a)$ - $\Delta cta(S40_{b,c}) < -5\%$, else: white colour.

On the other hand, a strong increase of irrigated area in a particular basin not necessarily implies a strong increase in cta as can be seen by comparing the left and right hand side of figure 5.8. One obvious reason is, of course, that a large relative increase of irrigated area might be small in absolute terms of water consumption. This naturally holds true for many basins in countries with barely developed water resources. Another, more interesting aspect is that basins with a more humid climate imply both lower irrigation water requirements *and* higher freshwater availability - likewise attenuating the increase in cta.

5.3.2 Interplay between suitability factors and constraints

All scenarios indicate that the most severe increases in water scarcity will occur in those regions which are already water stressed today, namely on the Mediterranean coast, the Nile basin, parts of the Orange and the Lake Chad basin, the Horn of Africa, some coastal basins in South Africa, and additionally in the Senegal River basin. In these regions, alternative basins with high suitability and low constraints are rare, and the pressure of irrigation expansion is high. This leaves no choice but to put additional pressure on water resources. This pressure is represented by the consumption-to-availability ratio (cta). If cta increases in a particular basin as a consequence of irrigation expansion, the preference values of all grid cells in that basin decrease according to equations 5.1 and 5.3 (value function for cta) – regardless of whether a cell is actually occupied by irrigated area or not. In the following, we refer to this effect as a “suitability loss”. A “suitability loss” on one grid cell is caused by multiplying the weighted sum of suitability factors (suitability) by the constraint value functions (see equation 5.1). The effect of suitability losses can be illustrated for an entire study area by computing the cumulative frequency distribution of preference values over the study area *before* and *after* the suitability values are being multiplied with the constraint value functions. Figure 5.10 shows an example breakdown of "suitability losses" as caused by the individual constraint factors, for the Northern African region (scenario S40a). It shows the cumulative frequency distribution of *suitability* in this region and how suitability is reduced when combined stepwise with the two constraint factors according to Eq. 5.1. First, we multiply the suitability value of each grid cell k with $g(c_{1,k})$. As a result, we see that suitability is considerably reduced - just because irrigation would not sufficiently pay off as compared to rain-fed cultivation. Subsequently, we compute the additional suitability loss caused by the constraining effect of cta in the year 2000, i.e. by multiplying $g(c_{2,k,t=2000})$. In the same way, we compute the suitability loss caused by the constraining effect of cta in the year 2050, i.e. by multiplying $g(c_{2,k,t=2050})$. By comparing the cumulative distributions after having applied $g(c_{2,k,t=2000})$ and $g(c_{2,k,t=2050})$, we can quantify the relative suitability loss that is caused by the expansion of irrigated areas between the years 2000 and 2050. Table 5.3 shows these losses for the different scenario variants: we find that the general range of suitability losses is between 20 and 25 % for Northern Africa and around 10 % for the entire African continent. The difference between S40a and S60 is quite low, bearing in mind that irrigation expansion until 2050 is 50 % higher for S60. This can be interpreted as an intrinsic effect of the value function $g(c_2)$ in its range of cta larger than 100 % (see figure 5.4): basins that already suffer high water stress in scenario S40a can also take some more irrigated area at low marginal suitability losses. To a certain extent, this is substantiated by comparing suitability losses for S40a and S40c. However, further sensitivity analysis is needed to explore broader ranges of change and additional value function formulations.

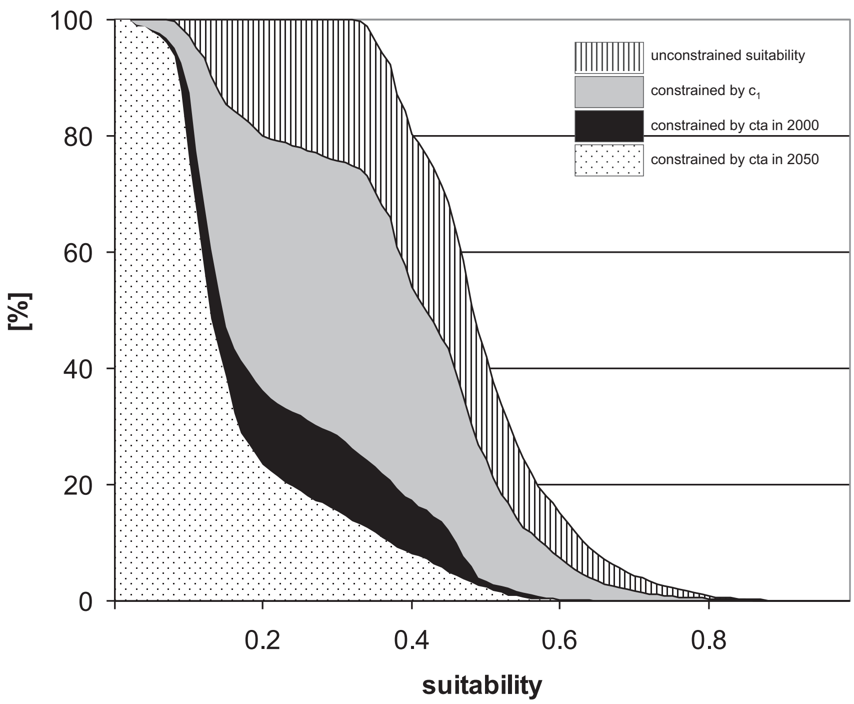

Figure 5.10: This figure shows the cumulative frequency distribution of suitability and constrained suitability for the example region Northern Africa and scenario S40a (i.e. percentage of the total area of the region falling into the different classes of suitability, class width = 0.01). Vertical hatching: unconstrained suitability acc. to Eq. 1; grey: constrained by factor c_1 (relative yield gain by irrigation); solid black: additionally constrained by cta in 2000; dotted fill: constrained by cta in 2050. The black area represents the additional loss in suitability due to irrigation expansion between 2000 and 2050.

Based on these findings, one could also think of a preference value as a proxy for the *vulnerability* of irrigated crop cultivation on a particular grid cell or in a particular basin. A lower preference value implies e.g. a lower soil fertility, higher salinisation or erosion risks, or a less reliable water supply (according to our suitability and constraint factors). Altogether, irrigated cultivation might be the more productive option, but the expansion of irrigated cropland can cause potential risks even in areas not yet occupied by irrigation.

5.3.3 Conceptual and data related uncertainties

Modelling a complex process such as the expansion of irrigated areas inevitably requires the simplification of many aspects – either because of incomplete understanding, or the lack of suitable methodologies or data. By assuming a *maximum allowable irrigated area per country*, we already exclude much of the complexity in the decision-making process (particularly from the economics and policy perspective). But even if we focus only on the simulation of spatial patterns, potentially important processes remain either unconsidered or their formulation remains uncertain. This type of uncertainty is generally referred to as "conceptual uncertainty" [El-Ghonemy et al., 2005; Olofsson and Fredriksson, 2005], or as structural [Rotmans and van Asselt, 2001] or model uncertainty [Smith, 2003]. Another type of uncertainty is induced by the underlying data ("data uncertainty"). In the following paragraphs, we discuss *selected* sources of both conceptual and data related uncertainty.

Conceptual uncertainty

We developed a simple, transparent approach to quantify the *impact of water depletion on the potential for further irrigation development* within a river basin. This approach integrates a variety of hydrological, climatic, socio-economic and societal factors. Further analysis should consider basin level time series of irrigation, run-off and consumption as well as significant socio-economic indicators. But such data are hardly available. More promising could be the consultation of water management experts and policy makers on basin, national and international level.

Irrigation is often applied to facilitate *multiple cropping* by extending the growing period beyond the rainy season [Kar et al., 2006; Turner et al., 2004]. Currently, our crop yield model considers only one cropping cycle per year. Consequently, we cannot adequately reflect the potential yield gains that can be achieved by applying irrigation. Although we implicitly consider this aspect in a very simple way in the preference ranking (factor c_1), it is also important to explicitly consider multiple cropping for the local production functions of each crop.

Irrigation is also adopted to increase *inter-annual yield reliability*, particularly in regions with unreliable rainfall [Negri et al., 2005]. Consequently, the quantification of rain-fed yield insecurity is important to assess the need for additional irrigation.

The *interplay between seasonal run-off regimes and crop water requirements* affects the feasibility of irrigation: peak demands for irrigation water do usually not coincide with peak flows of surface water. Although this can be dealt with by the establishment of storage capacities, there are certainly limits in the intra-annual redistribution of annual discharge [Turner et al., 2004].

Upstream-downstream linkages: concerning freshwater availability and consumption, we do not consider any spatial topologies *within* river basins. It is unclear how upstream-downstream topologies actually affect the sub-basin level: on the one hand, of course, upstream water consumption reduces downstream water availability. On the other hand, the accumulated availability is lower in upstream areas. Political implications are even harder to capture: there is clear evidence that upstream riparian states expand their water consumption by ignoring the interests of downstream riparians [Yoffe et al., 2003]. Nevertheless, upstream water management is often affected by bi- or multilateral international treaties [see e.g. Browder and Ortolano, 2000; Lamoree and Nilsson, 2000] or by downstream riperians exerting political pressure on upstream water users [Yoffe et al., 2004]. It is beyond the scope of our model to account for such complex political settings. Rather should we use it to identify regions and basins where such upstream-downstream relations should be analysed in more detail.

Finally, we ignore *inter-basin water transfer* due to the lack of adequate data. Water transfers between river basins are gaining importance, particularly in developing countries [Ghassemi and White, 2006; Jain et al., 2005]. The model structure basically would allow the definition of basin transfers in case adequate data become available in the future.

Data uncertainty

The location of current irrigated areas surely is uncertain: particularly in Africa, the map of irrigated areas published by Siebert et al. [2002] has limitations in data quality [Siebert, personal communication]. The construction of a preliminary map of crop specific irrigated areas (see appendix B1) is even more uncertain since it combines three uncertain sources (map of irrigated areas, crop distribution map, AQUASTAT country level data), additionally using a simple allocation methodology. There is an urgent need for crop specific maps of irrigated areas which are also consistent with census data.

Another source of uncertainty are the data provided by the WaterGAP model: concerning the simulated *annual renewable freshwater availability per river basin*, Kaspar [2004] carried out an extensive uncertainty analysis: he concludes that the uncertainty in water availability caused by uncertain model parameters is low compared to the uncertainty caused by the climate input data. Döll and Siebert [2002] document the computation of *irrigation water requirements* in the WaterGAP model and discuss potential limitations. For the LandSHIFT model, an important improvement would be to better account for the water requirements of specific crops, ideally in consistence with the simulation of crop yields and water flows in the DayCent model.

Finally, the simulation of *crop yields* is also subject to multiple uncertainties: please refer to Stehfest et al. [submitted] for an extensive discussion of potential uncertainties and errors.

5.4 Conclusions and Outlook

This paper introduces a methodology to simulate the spatial dynamics of irrigated areas, integrated in a framework for modelling large scale land use-change (LandSHIFT). The methodology is data-driven and scale-sensitive. It gets by with a minimum set of assumptions and produces encouraging validation results. It allows the specification of important system inputs such as drivers, suitability or constraint factors, as well as the modification of value functions or factor weights.

By considering water scarcity as a constraint to the expansion of irrigated areas, we represent an important feedback mechanism which influences the spatial dynamics of irrigated areas. In addition, the effect of water scarcity allows us to account for the competition between different water using sectors: the cta-ratio increases regardless of the additional water consumption originates from industry, households or agriculture. So additional water consumption e.g. from industry consequently will constrain irrigation expansion. As already pointed out, future research could also involve water management experts in participatory processes in order to re-evaluate or modify the quantitative effect of cta on irrigation expansion.

We emphasize that the model results are not to be understood as a *prediction* of future irrigation patterns, but rather as a means to identify general spatial trends in a consistent and transparent modelling and data framework. We are fully aware of the variety of potential uncertainties and errors contained in this methodology (see 5.3.3). Analysis and minimization of both conceptual and data related uncertainties is the major challenge to improve the presented methodology.

Despite these potential improvements, the model is available and ready for scenario analysis of land-water linkages in the context of global change. It can be used to address questions that require an integrated systems view, e.g. to analyse how water consumption from other sectors affects irrigation expansion. The impacts of climate change on the irrigation sector can be analysed at the interfaces of water availability, irrigation water requirements, potential crop yields and yield reliability. Another level of complexity will be achieved when the different sub-modules of LandSHIFT are applied in an integrated run, so that we can analyse e.g. the effects of urban sprawl on the displacement of irrigated cultivation – a prominent process e.g. in Egypt [Hanna and Osman, 1995]. Finally, the model can now be applied to other continents and on the global scale.

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CHAPTER 6

Synthesis

The major objective of this thesis was to develop data sets and methodologies for the simulation of cropland changes within a newly developed framework for global land-use modelling (LandSHIFT), particularly focussing on changes in irrigated land. For this purpose, we identified key research tasks: the analysis of the current state of large scale land-use modelling, the modelling of global crop yields, the mapping of global crop distribution and the development and implementation of a method to simulate the spatial distribution of irrigated land. We will now summarise our findings related to the aforementioned issues (6.1). The final chapter will highlight some particularly pressing research needs which emerge from the integrated consideration of all chapters (6.2).

6.1 Summary of findings

The state of continental to global land-use modelling

For our review, we selected 18 available modelling approaches and classified these by taking the integration of geographic and economic knowledge as a guiding principle. It turned out that economic approaches are particularly strong in the formalisation and integration of drivers on the demand side. They also provide a formalised structure to represent the competition among different sectors and are highly suited to reflect the shift of land requirements between regions as a consequence of global trade. Unfortunately, economic models do not yet fully utilise their potential to address endogenous changes in management and technology with respect to land-intensive sectors. Geographic models have their strengths in considering fundamental constraints on the supply side, particularly in terms of available land resources (not yet in terms of water resources) and their productive potential. Beyond, geographic approaches are highly suited to assess the impacts of land-use changes, e.g. the loss of natural habitats as a result of agricultural expansion.

Integrated models seek to combine these strengths in order to make up for the intrinsic deficits of both approaches and thus to assess the feedbacks between terrestrial environment and global economy. But despite the achievements and individual strengths of the selected modelling approaches, core problems of large scale land-use modelling have not yet been resolved: scaling issues are rarely explicitly addressed. The same applies to the aspect of inter-sectoral competition for land resources and the issue of endogenous representation of intensification processes. And finally, the question is yet unsolved how environmental and land-use changes might feed back to the decision-making of societies, institutions or other land-use agents. Altogether, continental to global scale models of land-use change do not yet satisfy the fundamental need for assessments on such scales (though currently, several new approaches are under development). Many of the reviewed approaches do not even consider the assessment of land-use changes and their impacts as their primary focus. For a new generation of integrated, large-scale land-use models, a transparent structure would be desirable which avoids redundancies and clearly employs the discussed advantages of both geographic and economic modelling concepts within one consistent framework.

Modelling global crop yields

Considering both crop growth *and* the related fluxes of carbon, nutrients and water is a precondition to consistently simulate crop yields *and* the environmental impacts of crop cultivation under specific management regimes. In other words, an integrated simulation of the plant/soil/atmosphere system is required. Constraints in data availability and computational capacity have so far hindered the application of such detailed simulations on the global scale.

We adapted and applied the process-based agro-ecosystem model DayCent to simulate global crop productivity. This provides us with a tool to consistently address crop yields, crop management, and fluxes of water and matter. As a first application, we computed global yield distributions of wheat, maize, rice and soybeans. By comparing the simulation results against FAO census data and a selection of regional maps, we showed that the DayCent model is able to reproduce the major effects of climate, soil and management on crop productivity (agreement of average simulated crop yields per country with FAOSTAT yield levels: $R^2 \approx 0.66$ for wheat, rice and maize; $R^2 = 0.32$ for soybeans). Beyond, spatial patterns of simulated yields mostly correspond to observed crop distributions and sub-national census data. It is the first time that a global crop yield model is tested in such detail. The tests do not only indicate the model quality, but also help to reveal uncertainties and potentials for improvement: this applies to both the input data and the representation of processes influencing crop growth: further model improvement will be achieved by refining the formulation of water stress and its effect on crop growth, by including phosphorous limitation for legumes, and by accounting for the effect of slope on surface runoff, water and nutrient availability. With respect to input data it became evident that the diversity of agricultural management at the global scale should be accounted for by implementing regional differences in crop varieties. For large countries, the diversity of management practices (e.g. fertiliser application rates) on the sub-national should be considered (however, adequate data is not available, yet). Beyond, management practices such as multiple (or sequential) cropping and crop rotations are not only relevant for soil nutrient balances, but also affect the determination of planting dates. Hence, it is important to represent these practices in future model versions, too.

Mapping global crop distribution

A new mapping methodology was developed to represent the global distribution of 17 major crops (plus grazing land). This methodology was designed to meet the following criteria: high spatial resolution (five arc minutes); consistency with FAO country level data of arable land, specific crop areas, and grazing land; definition of dominant land-use types per grid cell in order to enhance applicability in global assessment models such as LandSHIFT; consideration of the best available sub-national census data in order to adequately reflect crop distribution patterns. Beyond, our mapping study was the first to quantitatively compare its results against other available sources.

The methodology consists of a hierarchical process which allocates country level crop areas (as provided by FAOSTAT) on a five arc minutes grid. The general crop distribution pattern within a country is derived from sub-national census data, while the allocation procedure also takes into account information from remote sensing and crop suitability assessments. The product is widely consistent with available expert knowledge provided by USDA and GIEWS. The pixel-by-pixel comparison with another available global dataset published by Leff et al. [2004] revealed discrepancies as a result of different mapping approaches and input data. However, the agreement at lower spatial resolutions (30 to 60 arc minutes) indicates a substantial similarity of large scale patterns.

Mapping the global distribution of major crops is only one step forward towards the characterisation of agricultural land use as *farming systems*. Such a characterisation should not only include major crop types, but also typical management practices: e.g. crop rotations, occurrence of multiple cropping, and input levels of e.g. irrigation water or fertiliser.

Modelling the spatio-temporal dynamics of irrigated areas in Africa

Irrigation plays an important role for both global food security and the environmental impacts of agriculture. Globally, the irrigation sector is the main water user, but it is increasingly exposed to competition by other water using sectors. Considering the significance of irrigation, it is important to explicitly account for irrigated crop cultivation in large scale land-use modelling. To date, this has only been accomplished by the IMPACT model which – due to its characteristics as a global partial equilibrium model – only roughly accounts for the factors determining the potential for irrigated cultivation.

LandSHIFT is the first global, spatially explicit land-use model to incorporate both rain-fed and irrigated crop cultivation. To achieve this objective, we developed and implemented a methodology to simulate the spatial dynamics of irrigated areas and applied it in an exemplary case study for the African continent. Simulated changes in irrigated areas are exogenously driven by food demands, general trends in irrigation expansion and technological development (which are all specified on the country level). The spatial allocation of irrigated areas on a five arc minutes grid is governed by a set of spatial factors such as river network density or terrain slopes which are evaluated by means of Multi-Criteria-Analysis (MCA). The actual allocation procedure is based on a Multi-Objective-Land-Allocation (MOLA) algorithm and considers both rain-fed and irrigated land. An essential and innovative feature is the dynamic consideration of water limitation: in each river basin, an increase in irrigated area reduces the availability of water for additional increments of irrigated area. This directly affects the irrigation potential in subsequent time-steps. In other words: an intrinsic feedback mechanism dynamically influences the preference patterns for irrigated areas. Preference patterns were computed by splitting the African continent into sub-sets for calibration and validation. Validation on the second sub-set employed the *relative operating characteristic* (ROC) approach and produced an excellent agreement of preference patterns with the current distribution of irrigated areas.

Our methodology was applied in an exemplary case study for the African continent by simulating different scenarios of irrigation expansion and by applying different formulations of the water scarcity constraint. Generally, we could observe heterogeneous patterns of change within countries as a direct consequence of distinct preference patterns. All scenarios indicate that the most severe increases in water scarcity will occur in those regions which are already water stressed today. Besides, we found out that it is essential to include the feedback of water scarcity in order to avoid unrealistic concentrations of additional irrigated areas in only a few basins.

6.2 Need for future research

One important conclusion can be drawn from our previous findings: we need to enhance and systemise our perception of agricultural land use and its related dynamics. Aspects such as crop distribution, nutrient and water management as well as underlying socio-economic settings are not yet considered in a consistent context. One option would be to characterise these different aspects from the integrated perspective of *farming systems.*[a] The concept of farming systems as an analytical framework became common in the 1970s and it has contributed to a paradigm change in rural development thinking. But only recently, first attempts have been made to advance the geo-referenced characterisation of farming systems on large spatial scales [Dixon et al., 2001]. So how can large scale land-use modelling benefit from this development? The characterisation of agricultural land-use from a systems perspective neither is an end in itself nor is it just another descriptive framework. Its potential to advance existing concepts of land-use modelling lies within

[a] A farming system can be defined as “a population of individual farm systems that have broadly similar resource bases, enterprise patterns, household livelihoods and constraints […]”, where a farm system is referred as an “individual farm, its resources, and the resource flows and interactions”. Depending on the scale of analysis, a farming system can encompass a few dozen or many millions of individual farms. [Dixon et al., 2001]

its holistic viewpoint. The dominance of a major crop is only one system property. Management intensity (in terms of labour, but particularly in terms of water and nutrient inputs) is another. From a farming systems view, these properties have to be seen in the context of prevailing environmental constraints and socio-economic settings (such as tenure regimes, livelihoods, rural-urban linkages etc.). From a modelling perspective, this would allow to explicitly deal with coping capacities and vulnerabilities towards global environmental change, but also to understand the environmental impacts of land use as a consequence of particular system properties. Such an holistic view would break ground to consistently address questions such as: where will farmers be able to adapt to environmental changes (such as climate change) by sustainable management strategies? Where will these changes rather trigger further resource degradation as a result of limited coping capacities? Accordingly, the Science Plan of the Global Land Project expresses the need for "a concerted effort […] to develop a functional classification of these [management] practices in terms of their effects as disturbance regimes" [GLP, 2006]. In other words: a consistent, holistic system classification contains important a priori information of potential dynamics and development pathways and can thus be considered a key to simulate changes in land use.

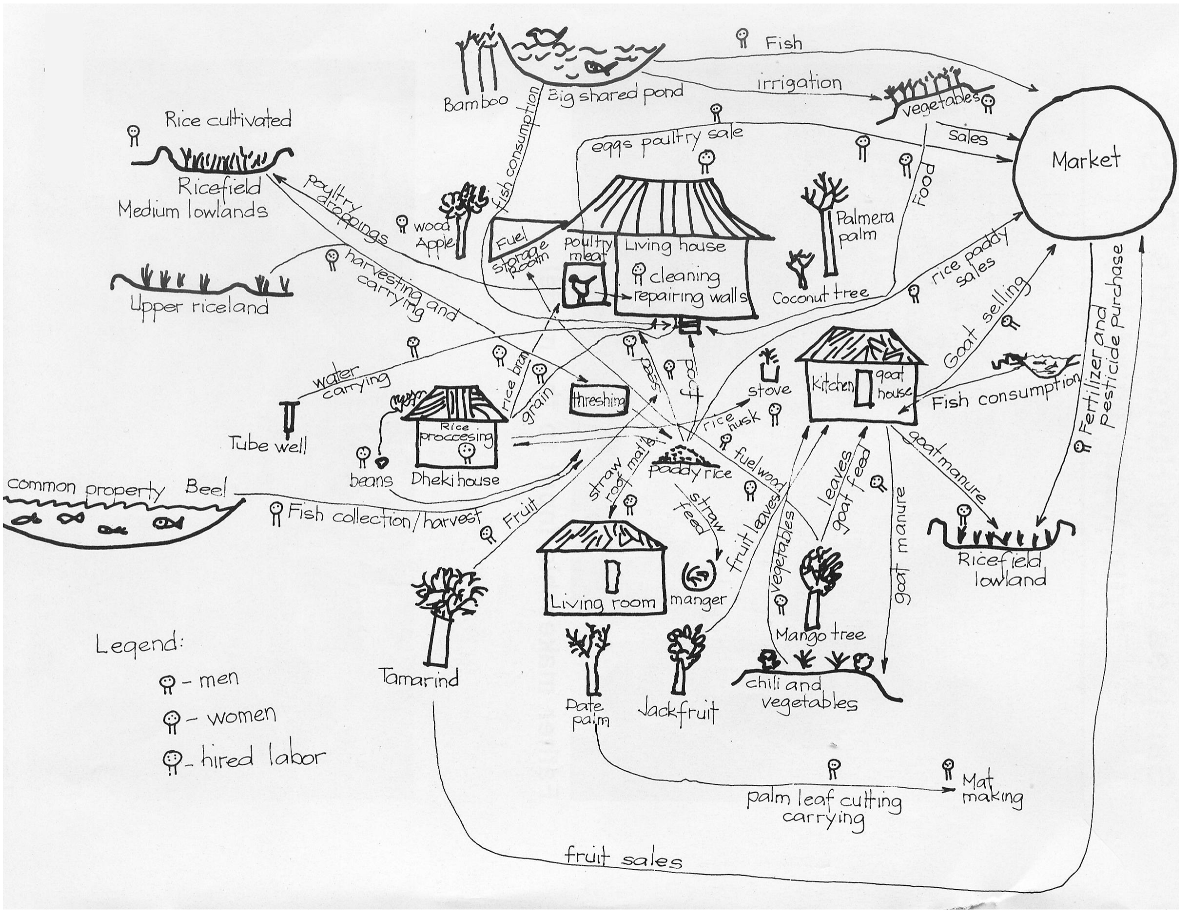

Figure 6.1: This system diagram was drawn by Bangladeshi farmers and illustrates the relations between various components of a smallholding [source: Lightfoot et al., 1991]. It also shows the variety of natural resources available to farm families. These resources normally include different types of land, various water sources and access to common property resources – including ponds, grazing areas and forest. To these basic natural resources may be added climate and biodiversity, as well as human, social and financial capital.

Particularly rule-based, heuristic modelling approaches have the flexibility to integrate these concepts into their rule sets. Nonetheless, the modelling community is still hesitant to adopt such an holistic viewpoint since it is, yet, rather expressed in qualitative than in quantitative terms. Thus, it remains a major challenge to integrate quantitative and qualitative information from various sources (e.g. census, remote sensing, regional experts) at various spatial levels (e.g. regions, administrative units, grids, basins) by using the farming systems concept as a guiding principle. In this context, the scale transition is particularly demanding, i.e. to abstract from small scale properties of farming systems (as shown in Figure 6.1) to an adequate definition of system properties and their interrelations on large spatial (and temporal) scales.

In the following, we would like to exemplify the need for a more integrated characterisation of agricultural land use by discussing the relevance of *multiple (or sequential) cropping* and its potential consideration in the studies presented in this thesis:

As already discussed, *multiple cropping* is an important issue for modelling irrigated areas, because irrigation is often applied to extend growing periods beyond the rainy season. However, multiple cropping is also crucial beyond the modelling of irrigated areas: the decision whether to cultivate new land or to intensify management on existing agricultural land fundamentally determines the characteristics of land-use change and its impacts on habitats, nutrient balances or water cycles. But for an improved representation of multiple cropping, crop mapping and crop yield modelling have to be involved. As for the crop yield simulation, a first step would be to identify potential areas of multiple cropping based on the concept of climate envelopes. Subsequently, the determination of planting dates would have to be adjusted to consider multiple cropping conditions (in practice, planting dates are often adapted to multiple cropping cycles or particular crop rotations). Based on such preparatory work, the DayCent model could be applied to quantify the potential contribution of multiple cropping to crop production and to investigate the implications for soil nutrient dynamics. But on the other hand, a favourable climate does not necessarily imply that multiple cropping is actually employed. Farmers might stick to a single cropping cycle per year as a result of input limitations in labour, capital or water. In this context, crop mapping could contribute to identify areas where multiple cropping is actually carried out. One strategy could be to make use of abundant remote sensing data: it has already been shown that the intra-annual variation of spectral signatures allows for an identification of multiple cropping cycles [Schweitzer et al., 2004]. It has even been shown that it is possible to identify irrigated areas from remote sensing data [Thenkabail et al., 2005]. Altogether, the use of remote sensing has to be considered as increasingly capable to contribute to a more differentiated characterisation of agricultural management (however, to expand such an analysis to the global scale remains a challenging task). Finally, the comparison of actual and potential areas of multiple cropping could provide insights about factors stimulating or constraining the application of multiple cropping – which would finally add to a more systematic characterisation of management practices in large scale studies.

In this context, it should be noted that the consideration of multiple cropping in the DayCent model is also an important prerequisite to simulate irrigation water requirements. At the moment, the irrigation water requirements applied in LandSHIFT are based on results from the WaterGAP model. Simulating both irrigated crop yields *and* crop specific water requirements with the DayCent model would not only enhance the consistency between LandSHIFT and DayCent, but would also allow to explicitly address the issue of water productivity. However, by including only one cropping cycle per year, the irrigation water requirements in many tropical and sub-tropical regions will be fundamentally underestimated. Beyond, we should refine the representation of crop specific transpiration fluxes in DayCent (which would also allow for an improved representation of plant water stress (as the ratio between actual transpiration and potential transpiration requirements).

Apart from the issue of farming systems, another important improvement would be to link the LandSHIFT model to a model of global trade. Chapter 2 comprehensively expressed the need to integrate economic and geographic expertise in order to adequately represent the process of land-use change. We will not resume this discussion, here. Nonetheless, we would like to give an example how to advance this kind of integration for the irrigation sector. In both chapter 2 and chapter 5, we mentioned the IMPACT agricultural trade model [Rosegrant et al., 2002] and its ability to simulate changes in irrigated areas for 36 world regions, based on an integrated consideration of supply and demand side drivers. A closer coupling of LandSHIFT with the IMPACT model could not only improve the simulation of cropland dynamics in general, but particularly the simulation of irrigation dynamics: the IMPACT model accounts for economic efficiency in linking demand with supply by considering global trade as well as investment policies. Based on that, it can provide general trends in irrigation expansion to the LandSHIFT model. Using the LandSHIFT model, these trends in irrigation expansion can be allocated to the grid level. Subsequently, information about the limitation of land and water resources could be derived and fed back to the IMPACT model in order to adjust the exogenous terms in the production functions which reflect the availability of land and water. Enabling such a dynamic data exchange would be a major leap forward in global land-use modelling - with respect to economic and geographic model integration, but also with respect to cross-scale integration (linkage between regional land/water resources and global trade).

But also without these improvements, the basic methodological framework is available and should now be tested and applied to other continents and at the global scale. Its design allows the flexible inclusion of additional knowledge about land-use change processes in different land intensive sectors. Beyond, the innovative capacity of the LandSHIFT model will only be fully utilised if all land-intensive sectors will be simulated in integrated runs. Such an integration would allow to explicitly address the synergetic interaction between different drivers of land-use change and between different types of land-use changes. The existence of such synergies is one of the main qualitative insights from the LUCC project [Lambin and Geist, 2006]: processes like agricultural expansion, urban sprawl and deforestation are often interlinked, e.g. as causal chains: agricultural expansion often follows the patterns of deforestation in tropical forests, accompanied by the expansion of settlements. On the other hand, different land-use types such as urban land or agriculture compete for the same land resources. Altogether, it will thus be particularly interesting to investigate the spatial interaction of different types of land-use changes. The representation of this interaction can be considered a key aspect to identify hot spots of land-use change as well as the related environmental consequences.

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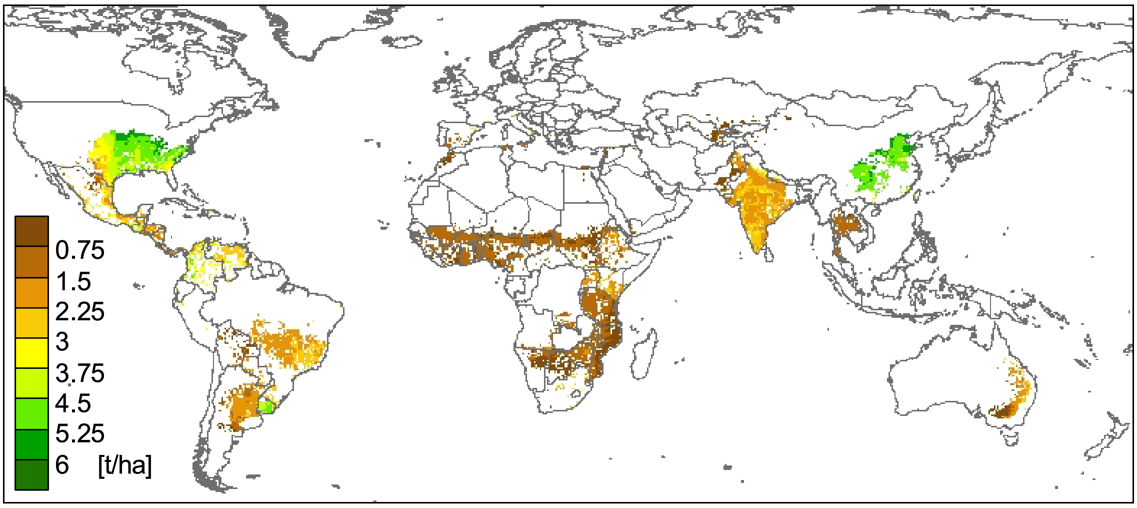
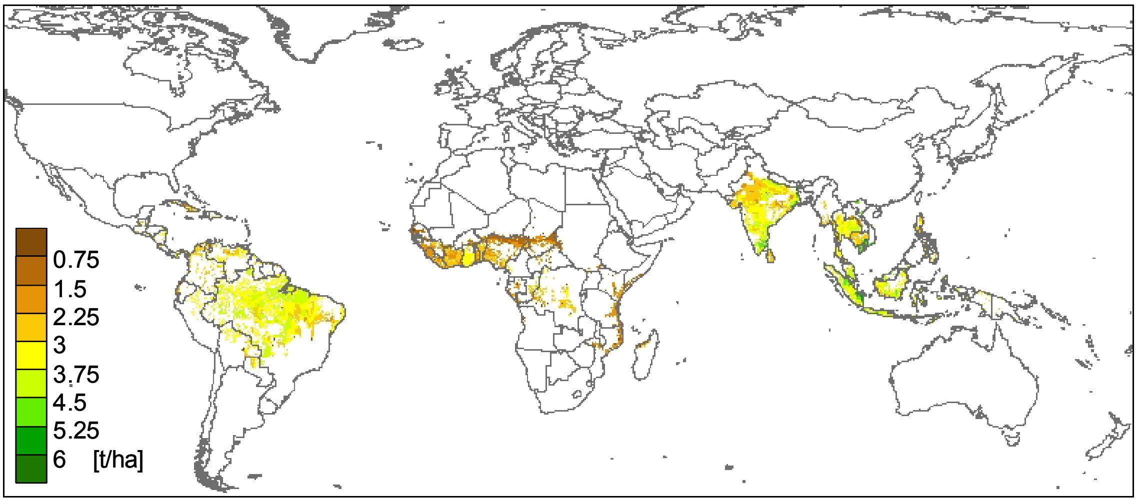
Appendix A: Simulated yields for tropical cereals, cassava, potato, pulses and cotton

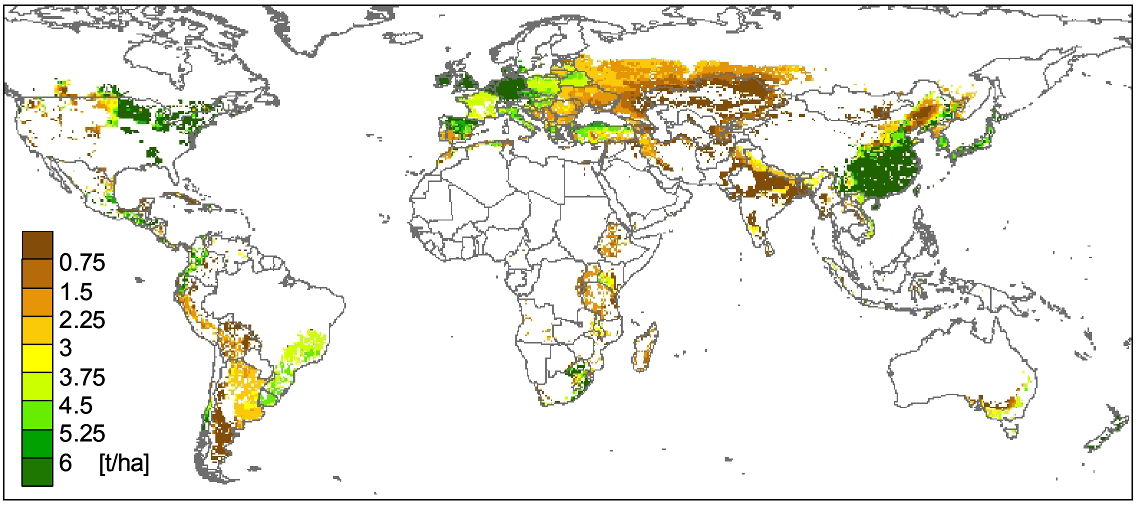
Layers are masked with Leff et al. [2004]



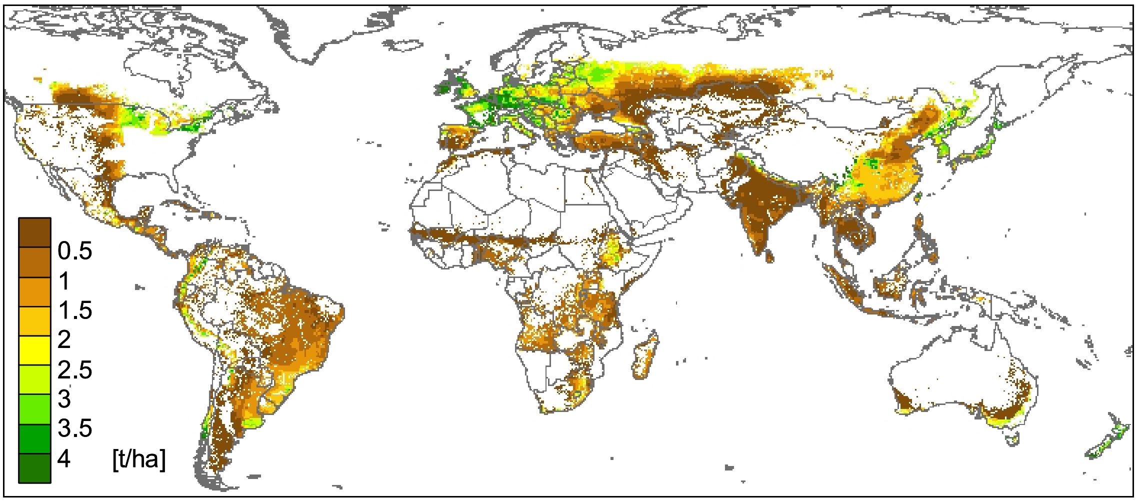
Sorghum and Millet: Yields simulated by the Daycent model for rain fed cropping [t ha^{-1}]



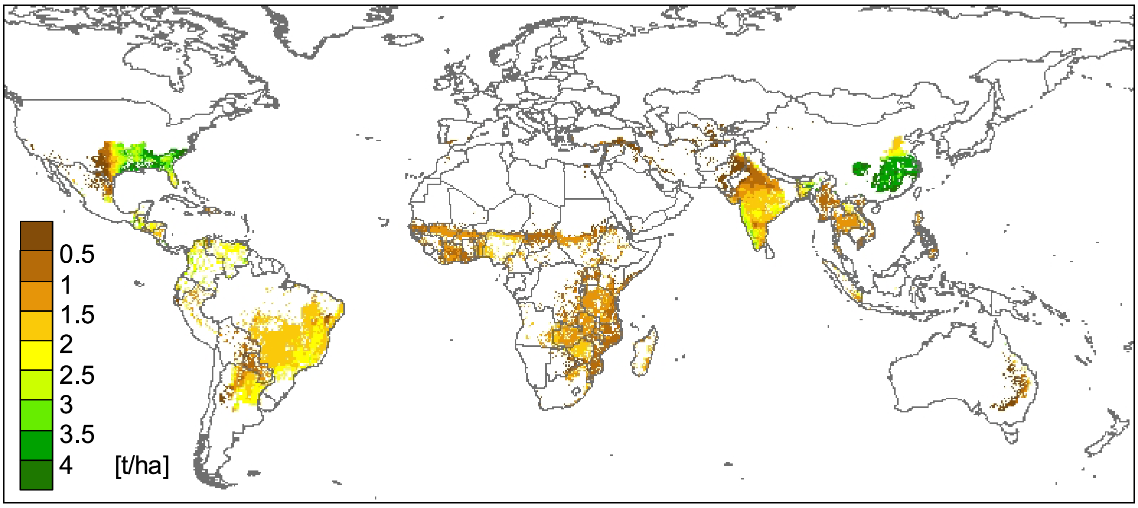
Cassava: Yields simulated by the Daycent model for rain fed cropping [t ha^{-1}]



Potato: Yields simulated by the Daycent model for rain fed cropping [t ha^{-1}]



Pulses: Yields simulated by the Daycent model for rain fed cropping [t ha^{-1}]



Cotton: Yields simulated by the Daycent model for rain fed cropping [t ha^{-1}]

Appendix B: Further aspects of modelling the spatio-temporal dynamics of irrigated areas in Africa

B1: Generating an initial condition for the crop specific distribution of irrigated areas

For this study, we needed a map which represents the distribution of major crops on a five arc minutes resolution as well as the information to which extent a crop is irrigated within a particular grid cell. On continental to global scales, no such map exists. What *does* exist are maps of *either* the distribution of crops *or* the distribution of irrigated areas. The initial crop distribution used in LandSHIFT represents the mid 1990ies. It was generated by merging remote sensing data and sub-national and national census data, consistent with FAOSTAT data (Heistermann et al., submitted). For the crop distribution map, we assume that one grid cell is occupied by only one crop type, consistent with the data requirements of LandSHIFT (see section 5.2.1). On the other hand, Siebert et al. (2002) published a global map which represents the fraction of land equipped for irrigation per five arc minute grid cell.

Our objective for this study was to create a preliminary map which

1) conserves the initial crop distribution used in LandSHIFT,
2) represents the typical spatial irrigation patterns as given by Siebert et al. (2002)
3) represents the typical *irrigation ratio* of a crop on country level. This means: if - based on the desired map - the area of a particular crop and its associated irrigated area were summed up for a particular country, the result should reflect the typical share of that crop being irrigated within that specific country (e.g. 10 % of the maize in country xy is typically cultivated under irrigation). This country level information is provided on the AQUASTAT homepage [AQUASTAT, 2006].

Due to inconsistencies between the two aforementioned maps, the desired map cannot be attained by just intersecting both of them (unrealistic irrigation ratios would be the consequence). We thus developed a simple allocation algorithm which assigns a fraction of irrigated area to each crop cell in the map of Heistermann et al. This algorithm is designed as an iterative procedure constrained by the condition that the typical *irrigation ratio* is attained for every crop-country combination. The *irrigation ratios* are derived from the AQUASTAT data. If for a specific crop-country combination, no adequate information was available, the irrigation ratio was set to the ratio between total irrigated area and total arable land in that country. The iterative allocation procedure assigns irrigation predominantly in those areas which are intensively irrigated according to the map of Siebert et al. (2002). This is achieved by creating preference rankings for all cells of a specific crop within a particular country: the fraction of irrigated area from Siebert et al. (2002) is used as a preference value for each cell. Beyond, it is employed to derive the fraction of irrigated area to be assigned per grid cell.

B2: Split of African countries into a calibration and validation sub-set

For calibration and validation, the African countries were divided into two different sub-sets, one for calibration and one for validation. Our precondition was to use countries from each GEO-region in Africa in order to account for various geographic and socio-economic conditions. The following table B2.1 shows the final split.

Table B2.1: Split of African countries according to GEO-region

GEO region	Calibration sub-set	Validation sub-set
Northern Africa	Morocco, Sudan, Tunisia	Algeria, Libya, Egypt, Western Sahara
Western Africa	Guinea, Niger, Nigeria	Burkina Faso, Gambia, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Liberia, Mali, Mauritania, Senegal, Sierra Leone, Togo, Benin
Central Africa	Cameroon, Chad, Democratic Republic of Congo	Central African Republic, Congo Republic, Gabon, Equatorial Guinea
Eastern Africa	Kenya, Somalia	Burundi, Djibouti, Eritrea, Ethiopia, Rwanda, Uganda
Southern Africa	Botswana, Zambia, Zimbabwe	Angola, Lesotho, Malawi, Mozambique, Namibia, South Africa, Swaziland, Tanzania
Western Indian Ocean	-	Madagascar

B3: Mapping crop commodities to internal crop types

The changes in crop areas are driven by the demand for crop commodities and the related yield improvements through technological and management change. In this study, we use results from the Millennium Assessment scenario “Order from Strength” as computed by the IMPACT agricultural trade model (Rosegrant et al., 2002). On the other hand, we use yield layers which were calculated by using a global version of the DayCent model (Stehfest et al., submitted). And finally, the map created by Heistermann et al. (submitted) is used to represent the spatial distribution of major crops. The categories from the IMPACT model, our yield layers and the crop distribution map are incongruent and consequently had to be mapped to each other for this study. This is done by defining internal crop commodities which are then related to land-use types as well as IMPACT crop commodities and yield layers. The base year production of the internal crop commodities in the year 1995 was computed from FAO statistics by using the 1993-1997 average values and aggregating over the related FAO categories. In order to calculate the demand and yield changes from the IMPACT data, we relate the relative changes between 2000 and 2050 as computed by the IMPACT model to the internal crop commodities and the yield layers respectively. Note that the product mapping in LandSHIFT is flexible and not fixed. This allows a modification of mapping relations for specific study regions and applications.

Table B3.1: Mapping scheme for relating external input data to internal crop commodities

Internal crop commodity	Related FAO categories	IMPACT category	DayCent yield layer
Wheat	Wheat	Wheat	Wheat
Temperate cereals	Barley, oats, rye, buckwheat	Other grains	Wheat
Rice	Paddy rice	Rice	Rice
Maize	Maize	Maize	Maize
Tropical cereals	Millet, sorghum	Other grains	Sorghum
Pulses	Dry beans, dry peas, chick peas, lentils	Other grains	Pulses
Tropical roots and tubers	Cassava, sweet potatoes, yams	Aggregated over sweet potatoes, yams, cassava	Cassava/sweet potato
Temperate roots and tubers	Potatoes	Potatoes	Irish potato
Annual oil crops	Groundnuts, rape, sesame, sunflower a.o.	Oils	default crop layer (maize)
Default product	Cotton seed, sugarcane, fruits, vegetables, coffee, cocoa, tea, tobacco, oil palms, coconut, olives, soybeans a.o.	aggregating over sugarcane, vegetables, fruits, soybeans	default crop layer (maize)

B4: Changes in crop commodity demands and yields according to the MA "Order from Strength" scenario

Based on the mapping relations shown in Appendix B3, the following table B4.1 contains the demand changes for the IMPACT model regions in Africa, while table B4.2 contains the yield changes. All changes are for the year 2050 relative to 1995. Table B4.3 maps the IMPACT model regions to the country level. This relation was used to scale the changes from regions to countries.

Table B4.1: Relative changes [%] in demand for crop commodities from 1995 to 2050

Region	Wheat	Rice	Maize	Other grains	Temp. R&T	Trop. R&T	Oil crops	Default crop
North Africa	136	91	111	69	172	-59	219	140
Southern SSA	284	252	267	730	82	247	425	194
Central and Western SSA	274	470	292	389	184	266	272	245
Northern SSA	258	370	147	303	164	185	98	162
Egypt	38	60	63	4	137	35	101	100
Eastern SSA	490	257	227	358	196	236	402	227
Nigeria	255	361	169	279	96	139	248	222
South Africa	65	70	130	143	35	166	75	101

Table B4.2: Relative changes in yield for IMPACT crop commodities from 1995 to 2050

Region	Wheat	Rice	Maize	Other grains	Temp. R&T	Trop. R&T	Oil crops	Default crop
North Africa	72	85	58	24	80	58	58	49
Southern SSA	29	98	96	187	47	119	96	56
Central and Western SSA	82	189	148	151	93	105	148	60
Northern SSA	89	143	73	110	79	112	73	43
Egypt	1	27	35	25	48	13	35	21
Eastern SSA	104	102	96	74	82	111	96	64
Nigeria	72	147	91	90	66	63	91	79
South Africa	44	53	46	92	37	134	46	27

Table B4.3: Membership of African countries in the IMPACT model regions (source: Rosegrant et al., 2002)

IMPACT region	Country membership
North Africa	Algeria, Libya, Morocco, Tunisia
Egypt	Egypt
Eastern Sub-Saharan Africa	Burundi, Kenya, Rwanda, Tanzania, Uganda
Nigeria	Nigeria
Northern Sub-Saharan Africa	Burkina Faso, Chad, Djibouti, Eritrea, Ethiopia, Mali, Mauritania, Niger, Somalia, Sudan
Southern Sub-Saharan Africa	Angola, Botswana, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Reunion, Swaziland, Zambia, Zimbabwe
Central and Western Sub-Saharan Africa	Benin, Cameroon, Central African Republic, Comoros Island, Congo Republic, Democratic Republic of Congo, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Liberia, Sao Tome and Principe, Senegal, Sierra Leone, Togo
South Africa	South Africa

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