INFLUENCE OF DATABASE COMPLEXITY AND DIVERSITY ON GLOBAL CROP SUITABILITY

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PREFACE

Considering that land is a limited resource on our planet and that the world's increasing population needs to be fed on the one hand and ecologically relevant areas should be conserved on the other, it becomes apparent that more precise knowledge about our capacity to feed ourselves is necessary. For this reason, an integrated sustainable land use management project – LAMA – was initiated in 2010 funded by the Bundesministerium für Bildung und Forschung (BMBF) in order to understand where pressures may arise in the future. Within this project the GLUES consortium (Global Assessment of Land Use Dynamics, Greenhouse Gas Emissions and Ecosystem Services) shall provide guidance to regional project partners and provide a framework of mid- to long-term scenarios. One component of GLUES is to underpin global trade models based on general / partial equilibrium theories with a monetary value for the land resource as well as to model yields of economically relevant crops in view of climate change and the restriction of water resources (Helmholtz Centre for Environmental Research, 2009). For this purpose, it is not only necessary to know the caloric intake per capita needed to ensure food security, disregarding cultural differences in diets, or to assess maximum attainable yields on a local basis, but it is most important to gain knowledge about the most suitable locations for crop growth.

I was therefore glad to support the team at LMU, guided by Professor Mauser, in the difficult task of designing, implementing and validating a new methodology for the analysis of crop suitable areas on a scale of 1 x 1 km. We worked through the following steps:

1) Set up and provide a model framework for the analysis of crop suitable areas

2) Compare global soil and climate databases and provide the most suitable set for the crop suitability analysis today and in the future

3) Study the influence of competing land uses on the extent of crop suitable areas such as urban or protected areas

The output of this work can be found in the present dissertation which compiles the results of three publications. I have structured the work into four parts. First, I will give a general introduction of the topic, highlighting the historic development of crop suitability analysis and presenting the current global works in this field. Secondly, I will present the basic global datasets necessary for such undertaking contrasting their qualitative differences and the reasons for our choices in the selection of some of these. I will also discuss our implemented methodology of fuzzy logic and some techniques that were applied in the validation process common to most of the findings. Thirdly, I will present the major results of the findings of the publications. And lastly, I will discuss the implications that these findings have on our knowledge base.

My dearest regards go to Prof. Dr. Mauser who had clear ideas about the implementation of the concepts but gave me free handling in the final applications. Many thanks also go to my dear colleague Florian Zabel who was mainly responsible for the coding of the model. Without his skills this work would have taken much longer and would have lacked the present quality. I thank both Prof. Mauser and Dr. Zabel for the long hours of discussions and mental debates that were very enriching and inspiring. The best thing to do while fully clothed!

Moreover, I would like to thank my colleagues Dr. Heinzeller, Dr. Richter, Dr. Prasch and Mrs. Koch for their helpful insights and their comments on the publications. Moreover, I would like to highlight the work of our two student workers Mr. Ron Günther and Mrs. Birgitta Putzenlechner in terms of GIS work on global databases and plant parameterization of 15 crops, respectively. Further regards go to the three students that analyzed the issue of urbanization on three continents as a fulfillment of their Bachelor degree, namely Mr. Jonas Meier, Mrs. Veronique Nitsch and Mrs. Stella Haun, as well as to Mrs. Ariane Hartmann for the analysis of the Global Climate Model data with measured values.

Also, I would like to thank Wayne Elliott, my dear colleague at the World Meteorolgocial Organization, who has helped me in enhancing my English for the publications. Short sentences that deliver one message is key!

I would further like to thank my parents and in particular my mother for always being there when needed, be it during my trips to meet with project partners or to listen to the newest research findings. However, mostly, I need to thank my son Noah for allowing me to work and for being curious about it. I thank him for his patience, for forgiving me my temporary absences and for his understanding. It is for him and the generations to come that this research is most important.

I am confident that this work has broadened my horizon and given me tremendous insight into the wide roam of food security in these uncertain times. I believe that this knowledge will aid me in mastering future challenges that may arise in other work environments.

Summary

Crop growth depends fundamentally on biophysical factors such as topographic features, soil quality, temperature and precipitation. Understanding which crop can grow optimally at which point on this planet is crucial in our current global situation where roughly 1 billion people suffer from hunger and malnutrition each day. Population growth and the inherent urbanization lead to changing pressures on land uses and cause challenges in the production pathways. Shifting markets, such as the production of crops for fueling purposes and fodder for livestock, are altering the purposes of crop production.

In the research presented here, the intent was to show the crop suitable areas of 15 basic crops on a global scale given only biophysical parameters. We tried to answer the question: where would we grow which crop if we would only have the given biophysical qualities? We excluded enhanced growing conditions through fertilizers, greenhouses and irrigation. This is an intriguing exercise as we were actually able to show that those regions that are currently already in use for agricultural purposes are indeed the most suitable ones. Use of advanced production systems in these regions, further enhances yields, but suitable biophysical conditions are key.

Crop suitability analyses exist in various forms and formats, for specific crops in specific locations and in few instances at the global scale as in the case of the Global Agroecological Zones studies, a co-production between the United Nations Food and Agricultural Organization and the International Institute for Applied Systems Analysis (IIASA). We decided to test a methodology of sliding scales based on fuzzy logic methodologies. Given the complexity of global soil, topography and climate databases and their, often, error-prone data, applying strict boundaries to the abilities for a crop to grow under certain conditions, seemed inappropriate. Rather assigning possibilities of a crop to grow departing from its ideal conditions seemed more adequate.

Fundamental to this work was the scrutinizing analysis of the quality of the global datasets that were used. In particular, the soil databases showed to be of critical importance and their quality varied significantly in some geographic areas. It was also interesting to note that crop suitability was strongly influenced by the use of 1 or more soil component per pixel, with some pronounced regional differences. The climate datasets were in general less different and only showed variances in high mountain regions. For the topography a compromise between quality and geographic extent had to be struck.

Land use is subject to diverse pressures that often conflict with agricultural production. One such pressure is the growing urbanization of many fertile areas. We looked at the loss of crop suitable areas due to cities and were able to show that 1% of the highly suitable crop growth areas have already been engulfed by cities, with some regions being more affected than others. At the same time, currently protected areas based on all International Union for Conservation of Nature classifications cover 12 % of all crop suitable land.

Overall, this work demonstrates the importance of the quality of the underlying databases for the results. Using the fuzzy logic approach allowed obtaining high quality results on a small spatial scale (0.008°) despite the varying quality of the databases. This was demonstrated by comparing the outputs with the current distribution of agricultural land from satellite images and other historic records. More room for expansion of crops is found largely in Sub-Saharan Africa and South America

which is consistent with findings of other studies; while the importance of protected areas needs to be further taken into account.

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Introduction

The question of distributing crop suitable areas globally arises due to the pressing need to cope with synergistic challenges; the increase in the world's population to ca. 8.3 billion by 2030 (UNDP 2008), the necessity of resulting increased food production and the shift in diets to high calorie foods (Roy et al. 2006; Foresight 2011) as well as halving the world's population that faces hunger by 2015 as postulated by the Millennium Development Goals (http://www.un.org/millenniumgoals/poverty.shtml) and thereafter. At the same time, most of the arable land (roughly 12 % of the land surface) is currently under use and room for expansion is said to be tied down due to the lack of agriculturally suitable land on the one hand and the call for the conservation of natural systems on the other (Navin Ramankutty, Delire, and Snyder 2006; Fischer 2002; Foresight 2011).

Enhanced yields have been reported throughout the globe in the past 50 years as a product of the 'green revolution' as high yielding crop varieties, fertilizers, mechanization and irrigation took hold of the arable lands (IFPRI 2002). Nevertheless, yields have reached their maximum attainble practical potential for a variety of crops in most developed nations (Figure 1) (Foresight 2011; Jaggard, Qi, and Ober 2010; Evans 2003) thus putting even more pressure on improving production system in developing nations.

At the same time, room for expansion is no longer available in the industrial parts of the world and has almost reached saturation in Asia (Fischer 2002; Fischer 2000). Thus most expansion will take place in South America and Africa.

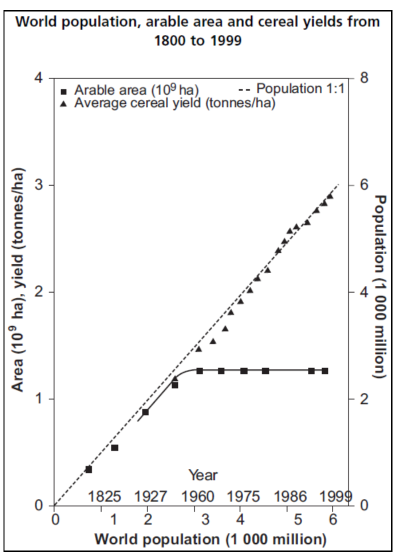

Figure 1: Imparity between world population increase and stagnating yields and production areas of cereals (Evans, 2003)

Studying where the most amount of room for improvement exists, is essential in order to prevent future food crisis and thus make concentrated economic actions possible (Evans 2003).

1.1 Historic development of land suitability classification

The basis of land suitability classifications was set in the 1970's when the FAO published their 'Framework for land evaluation' where land capability is the inherent capacity of land to perform at a given level for a general use and land suitability is set as the fitness of a given land for a defined use (FAO 1976). Here five suitability classes can be distinguished (Table 1), with three being suitable for agricultural production and two being non suitable (FAO 1976).

Table 1: Suitability classification according to FAO 1976

Class S1 Highly Suitable:	Land having no significant limitations to sustained application of a given use, or only minor limitations that will not significantly reduce productivity or benefits and will not raise inputs above an acceptable level.
Class S2 Moderately Suitable:	Land having limitations which in aggregate are moderately severe for sustained application of a given use; the limitations will reduce productivity or benefits and increase required inputs to the extent that the overall advantage to be gained from the use, although still attractive, will be appreciably inferior to that expected on Class S1 land.
Class S3 Marginally Suitable:	Land having limitations which in aggregate are severe for sustained application of a given use and will so reduce productivity or benefits, or increase required inputs, that this expenditure will be only marginally justified.
Class N1 Currently Not Suitable:	Land having limitations which may be surmountable in time but which cannot be corrected with existing knowledge at currently acceptable cost; the limitations are so severe as to preclude successful sustained use of the land in the given manner.
Class N2 Permanently Not Suitable:	Land having limitations which appear so severe as to preclude any possibilities Of successful sustained use of the land in the given manner.

This framework was lately adjusted mainly to include local stakeholder participation in the process of defining locally suitable areas (FAO 2007). Other systems include:

- **Fertility Capability Classification (FCC)** a technical soil classification system that focuses quantitatively on the physical and chemical properties of the soil that are important to fertility management (Sanchez, Couto, and Buol 1982)
- **Soil potential ratings** (Beatty 1979) classes that indicate the relative quality of a soil for a particular use compared with other soils of a given area.
- **Land Evaluation and Site Assessment (LESA)** used to define an approach for rating the relative quality of land resources based upon specific measurable features (Liang et al. 1986)}.

However, all of these frameworks are held in a general matter where suitability is not defined for a specific crop.

1.1.1 Fuzzy classification systems

Since the 1980's, the possibilities of manipulating large amounts of geographical information and remote sensing data has strongly increased. Burrough et al. with their principles of fuzzy logic for land suitability classification (Burrough, MacMillan, and Deursen 1992) and Rossiter et al. with their 'Theoretical framework for land evaluation' (Rossiter 1996), laid the foundation for a new kind of local to regional land and crop suitability study. In short, they claim that since most soil parameters have a large error rate per se, due to sampling and handling errors, and crops are able to grow at various levels of these parameters, strict Boolean classification systems may be too restrictive in growth ranges and areas, and that therefore **fuzzy classification** methods, where growth is defined through membership functions and likelihoods, should be applied (Figure 2).

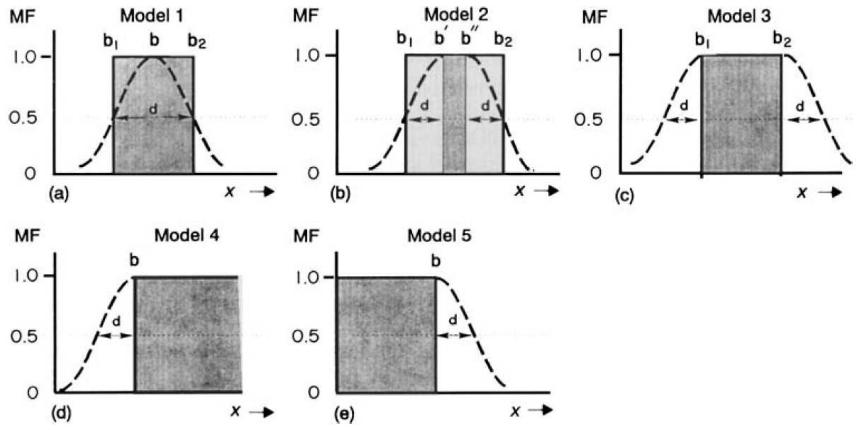

Fig. 1. Boolean and Fuzzy classification models. Horizontal axis: attribute value *x*; vertical axis: value of the membership function MF_x. The broken lines show the envelopes of the fuzzy classes for each model; the solid lines enclosing shaded areas indicate the equivalent Boolean sets. The main difference between the fuzzy and Boolean systems is that in fuzzy sets an individual receives a value on the continuous scale lying between zero and one, whereas for Boolean sets the value can only be one ('true') or zero ('false').

Figure 2: Overview of the differences between boolean and fuzzy classification models from (Burrough et al., 1992)

Most of these studies apply **Productivity Indices,** which are relative rankings of soil, terrain and climate conditions with respect to yield (Sys et al. 1993), to characterize the growing abilities of the used plants. They usually develop some kind of framework that allows the integration of different GIS based inputs, i.e. spatio-statistic methods such as krigging (Braimoh, Vlek, and Stein 2004) or the creation of indices (N. Ramankutty et al. 2008). Others underpin such information with expert knowledge, such as ALES (Rossiter 1996), LRIS (Verdoodt and Van Ranst 2006) or MicroLEIS (De la Rosa et al. 2004). In some cases Decision Support Systems are developed to facilitate the stakeholder dialogue (Ceballos-Silva and López-Blanco 2003; Baja, Chapman, and Dragovich 2002). In other cases, neural networks based on fuzzy logic are implemented (Xue et al. 2007) or models are directly implemented into GIS analyzing system such as ERDAS (Reshmidevi, Eldho, and Jana 2009), IDRISI (Ahamed, Rao, and Murthy 2000) and ESRI ArcMAP (Chen, Yu, and Khan 2010), or the combination of systems such as MATLAB with Surfer (Kurtener, Torbert, and Krueger 2008) or Visual Basic with MapObjects Active X (Kalogirou 2001).

1.1.2 Productivity index used in a global suitability classification

(Navin Ramankutty et al. 2002) from SAGE (Center for Sustainability and the Global Environment at the University of Madison, Wisconsin) used a combined index of climate and soil indicators in order to make inferences about the distribution of crops under current and future climate. They used an estimate of the days a plant needs to grow (also called growing degree days) under its geographically specific climatic conditions and measures of pH and soil carbon content for the soil physiological constraints and thus built a site specific quality index for crops in general on a 0.5 degree grid. Their data was based on the soil parameters from Global Soils Data Task Group of the International Geosphere-Biosphere Programme (Loveland and Belward 1998) in a 5 arc minute resolution and climate variables by CRU05 from the University of East Anglia with mean monthly climate conditions from 1961-1990 on a 0.5 degree grid resolution.

Thus land suitability for cultivation, S, is given by,

$$S = S_{clim} \times S_{soils} \qquad (10)$$

where:

$$S_{clim} = f_1(GDD) f_2(\alpha), \qquad (11)$$

and

$$S_{soil} = g_1(C_{soil}) g_2(pH_{soil}). \qquad (12)$$

They showed that crop suitable areas could be expanded by 120%, in particular in South America and Africa, albeit in areas that are currently under forest protection (Figure 3). Future climate conditions will most strongly affect areas that are currently already precipitation limited such as the Great Plains of the USA and north-eastern China.

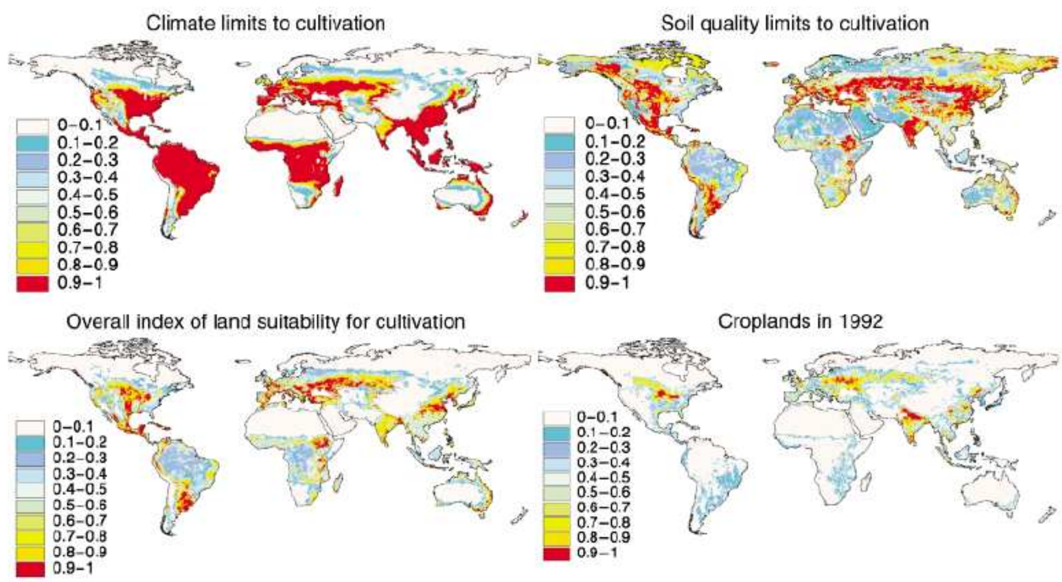

Fig. 4 Top panels: the climatic and soil quality limits to cultivation. The climatic limit is calculated by applying the GDD and moisture functions (Fig. 3) to their respective spatial data (Fig. 1). The soil quality limit is calculated by applying the soil carbon density and soil pH functions (Fig. 2) to their respective spatial data (Fig. 1). Bottom left panel: overall index of land suitability for cultivation derived as a product of the climate and soil quality limits to cultivation. Bottom right panel: the distribution of croplands in 1992, derived from Ramankutty & Foley (1998).

Figure 3: Geographically explicit limitations according to climate and/or soil constraints in comparison to the extent of croplands in the year 1992 from (Ramankutty et al., 2002)

1.1.3 Agroecological zones

Another approach of plant classification systems are the Agro-ecological zones (AEZ), which have been developed to visualize the plant adaptability to a certain region. This approach has been implemented in global studies, including the latest IIASA-FAO study (International Institute for Applied Systems Analysis), which defines areas of growth and yields for 28 crops/crop types through Land Utilization Types LUT's and according to the level of technology (high, intermediate and low inputs) (Fischer 2000; Fischer 2002; Tubiello and Fischer 2007) (Figure 4). The LUT's are defined by three criteria (a) crop characteristics (i.e. length of growing period LGP), (b) soil, terrain and climate constraints, (c) biomass to yield conversion.

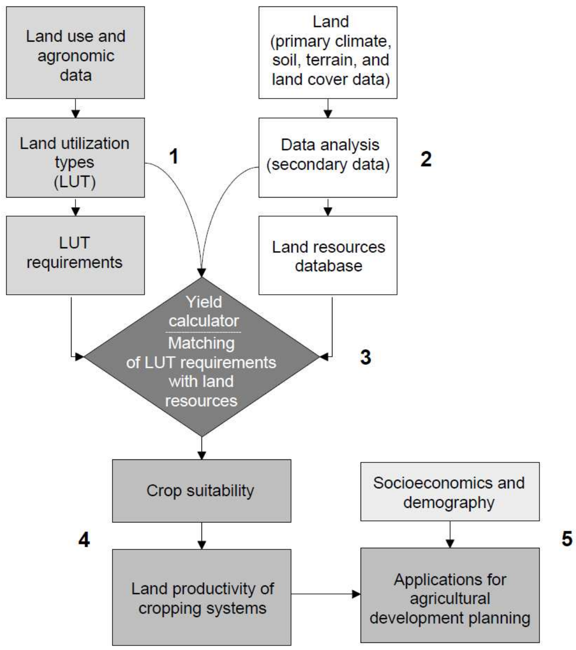

Figure 4: Conceptual framework of agro-ecological zones from (Fischer, 2002)

They used GTOPO data as terrain input, the Digital Soil Map of the World for soil variable input, and the CRU data for climate variables on a 0.5 degree resolution. In their latest version they have to the Harmonized World Soil Database (HWSD) (FAO/IIASA/ISRIC/ISSCAS/JRC 2009a).

They concluded that roughly 25 % of the Earth's surface is suitable for rainfed cultivation, considering a variety of assumptions such as the level of technology applied and the combination of these. Room for expansion is mostly found in South America and Africa with up to 20% of further agricultural extent (Fischer 2000; Fischer 2002).

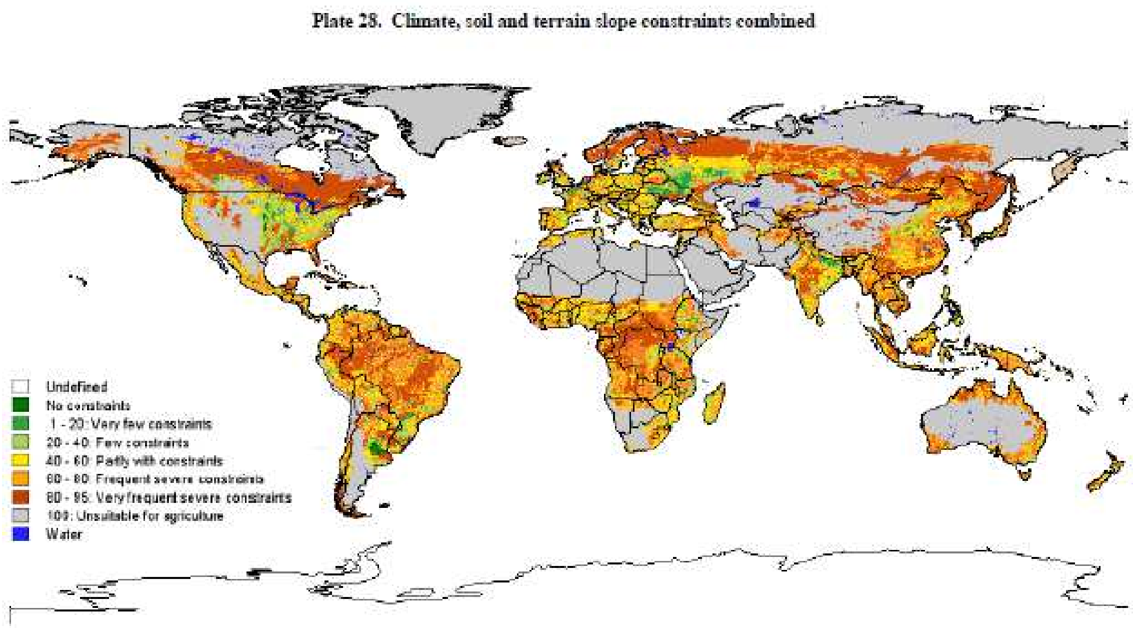

Figure 5: Global distribution of crop suitable areas, as in areas without constraints (green) (Günther Fischer, 2000)

1.2 Global Data Sets

Three main datasets are crucial for the analysis of crop suitable areas:

- Terrain (Digital Elevation Models)
- Soil
- Climate

In the subsequent sections, I will shortly present the main databases that were assessed and highlight their strength and weaknesses. The publications show the effect of the use of some of these datasets on the amount and distribution of crop suitable areas.

1.2.1 Digital Elevation Models (DEM)

a. USGS-GTOPO30

The United States Geological Survey's Center (USGS) has produced, in collaboration with many other agencies, a global digital DEM in 30 arc second (roughly 1km) resolution (http://eros.usgs.gov/#/Find_Data/Products_and_Data_Available/gtopo30/hydro). It is a compilation of diverse topographic information and covers the globe from 120W to 120E and from 85N to 64S divided into continental tiles, with the exception of continental Australia. Derived properties of topography such as slope, aspect, flow direction, flow accumulation, streams and drainage basins have been produced under HYDRO1K (Figure 6).

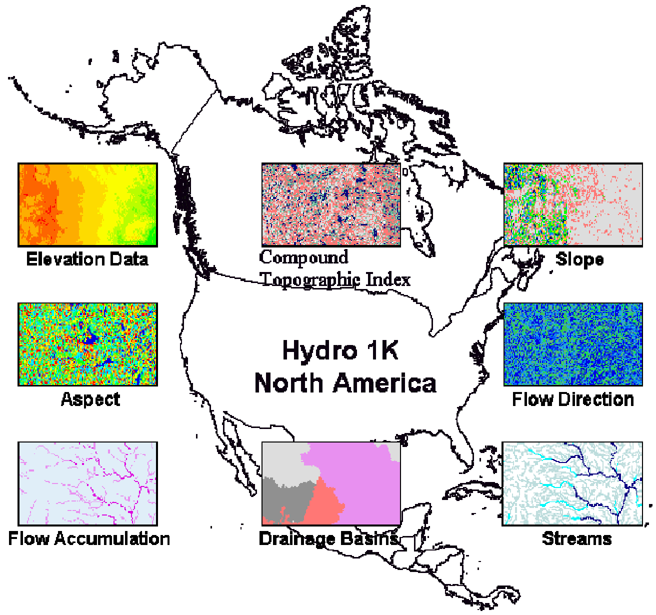

Figure 6: Derived topographical properties produced under the USGS-HYDRO1K database

Due to the fact that the DEM data is a digitized version of diverse topographic maps, in some areas, especially in the lowlands, elevation does not increase smoothly but in steps thus building terraces and influencing modeling quality (Figure 7).

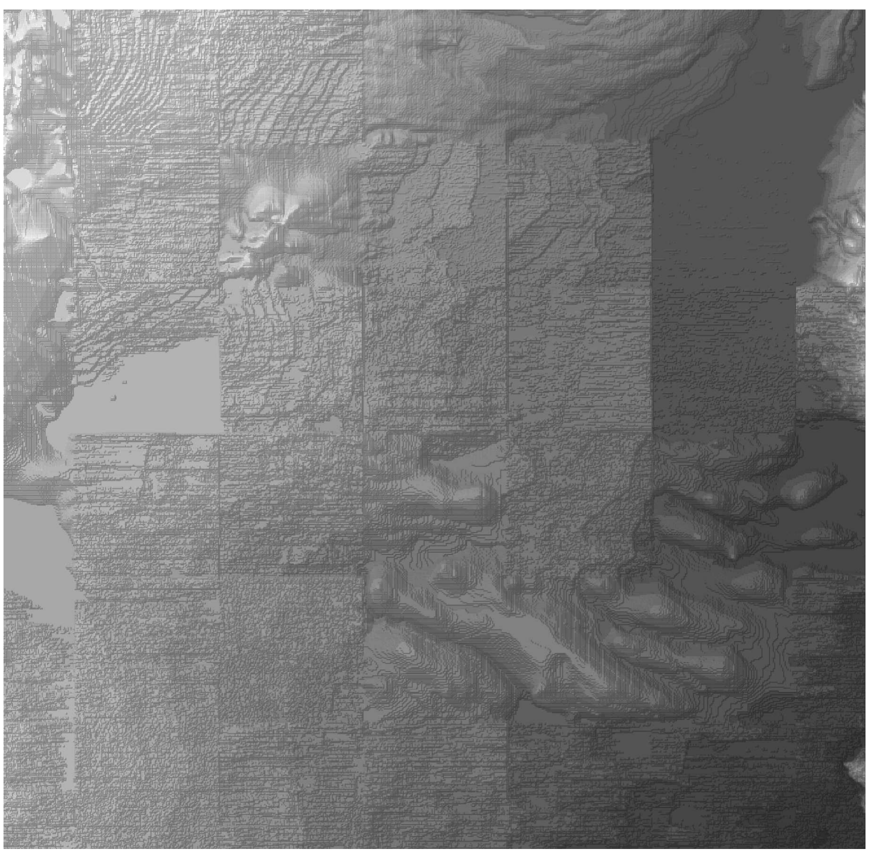

Figure 7: Excerpt of GTOPO-DEM of the Paraguayan Chaco region (60°W, 23°S) in hillshade view visualizing the change in height due to tiles and the digitalization process

b. Shuttle Radar Topography Mission - SRTM

Apart from the digitalization of maps for DEM, satellite missions have also attempted to grasp the changes in altitude of the globes surface. One such mission was the SRTM which was on board of the Space Shuttle Endeavour in the year 2000 and delivered topographical information in a 3 arc second (90m) resolution from 180W to 180 E and 60N to 60S (Farr et al. 2007). Thus, it is missing spatial information of Northern Canada, Europe and Asia (Figure 8).

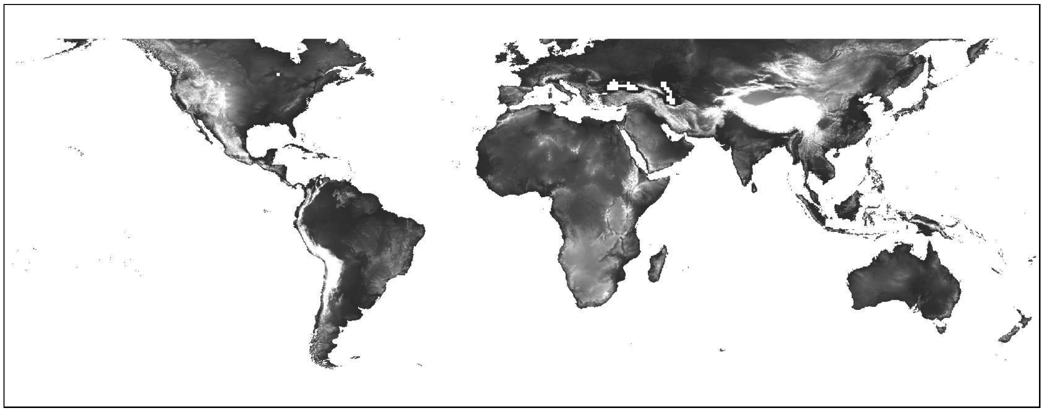

Figure 8: Overview on the extent of the SRTM DEM data showing that the polar regions are missing

Although, the SRTM does show tiling issues it is to a much less extent than the GTOPO and therefore more suitable for modeling purposes (Figure 9).

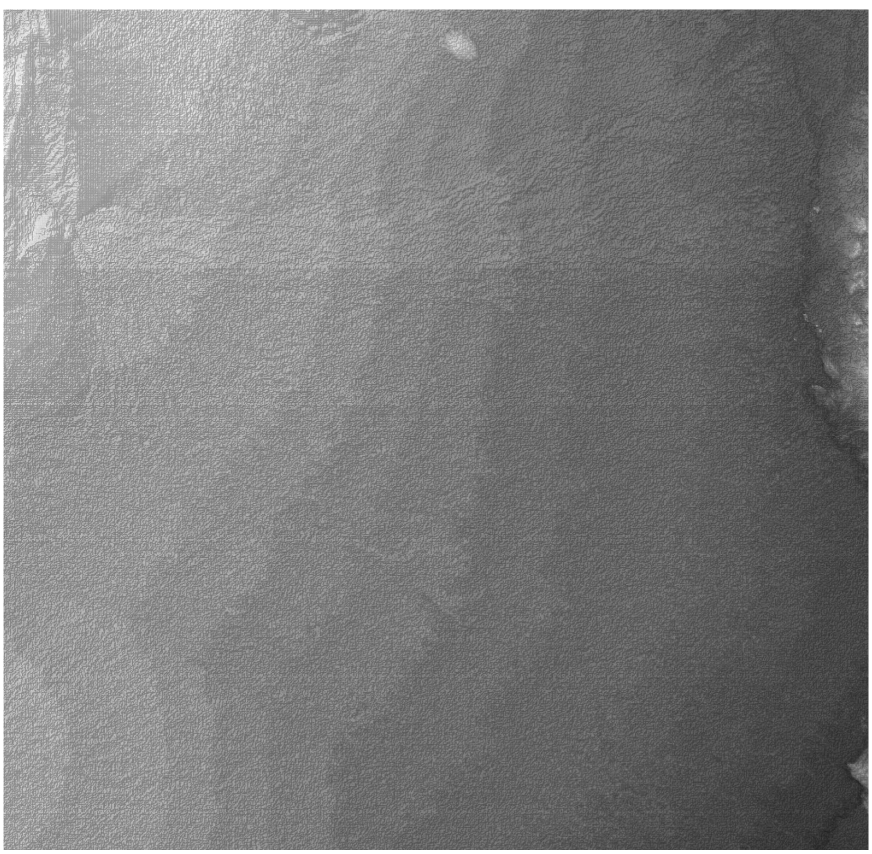

Figure 9: Excerpt of SRTM-DEM of the Paraguayan Chaco region (60°W, 23°S) in hillshade view

We therefore used the extended SRTM30 data, which merges high quality SRTM data with GTOPO data in the northern region where SRTM does not have coverage (i.e. between 60°N and 85°N) or where SRTM has faulty information (mountain tops, coastlines…) (http://dds.cr.usgs.gov/srtm/version2_1/SRTM30/).

We further computed the slope from the SRTM30 DEM (Farr et al. 2007; USGS 2000) applying an Eckhardt IV projection and bilinear resampling. The reprojected results (into WGS84) were compared with the HYDRO1K slope dataset (USGS 1996). Differences were mainly observed in steeper areas (mountains) and were neglectable in flat areas (Figure 10).

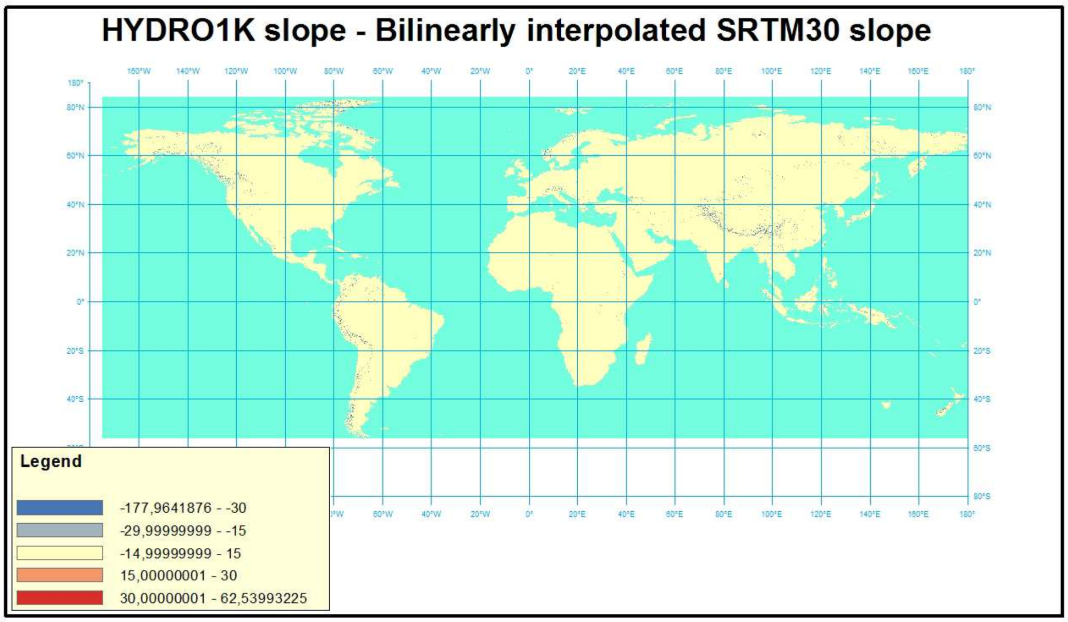

Figure 10: Difference in slope (%) between GTOPO HYDRO1k slope and bilinearly resampled projection of SRTM30 slope showing that only some differences existed in the high altitude areas.

1.2.2 Soil

For a thorough analysis of the differences between the different global soil datasets you may wish to read Mr. Günther’s Bachelor Thesis which I supervised during my PhD project (Guenther 2011).

a. Digitized Soil Map of the World - DSMW

The DSMW is the digital version of the FAO-UNESCO Soil Map of the World in a 1:5 000 000 scale, a first attempt to visualize soil classes on a global scale, and was developed in the 1970s (1971-1981) (Figure 11). It is based on the 1974 FAO soil classification (see Annex 1: Soil classification according to FAO 1974) which unified different soil classification system especially, between Europe and the USA.

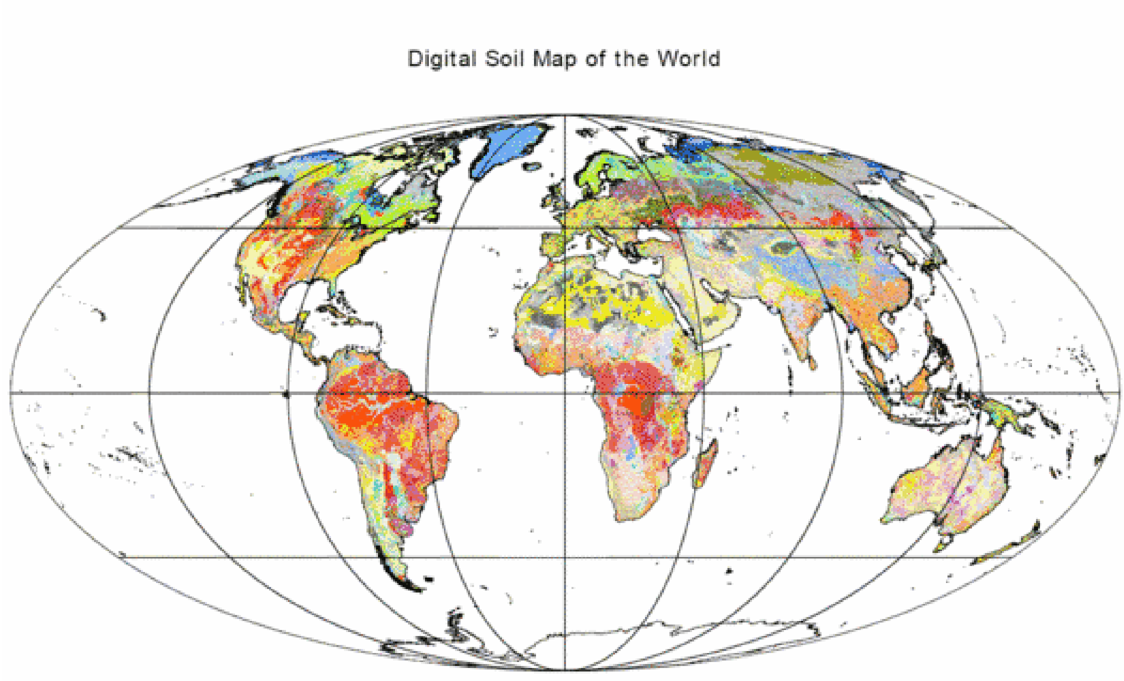

Figure 11: DSMW representation from

http://www.fao.org/fileadmin/templates/nr/images/resources/images/SoilMap_hires.pdf

b. ISRIC-World Soil Information

ISRIC is a Dutch institution devoted to soil data collection especially in South America, Africa and South East Asia (http://www.isric.org/). In their database ISRIC-WISE 3.1 they currently have more than 10.000 soil profiles from 149 countries (N. Batjes 2008). On the basis of this database and expert knowledge they have developed standardized taxotransfer rules (3.4.3 Taxotransfer scheme in (Batjes, 2003)) for which fixed parameter set values are assigned to each of the 126 FAO 1974 soil classification schemes and allocated geographically explicit according to their distribution within the DSMW.

This methodology results in the following representation of 126 FAO 1974 soil classes (Figure 12) grouped within 26 major soil classes:

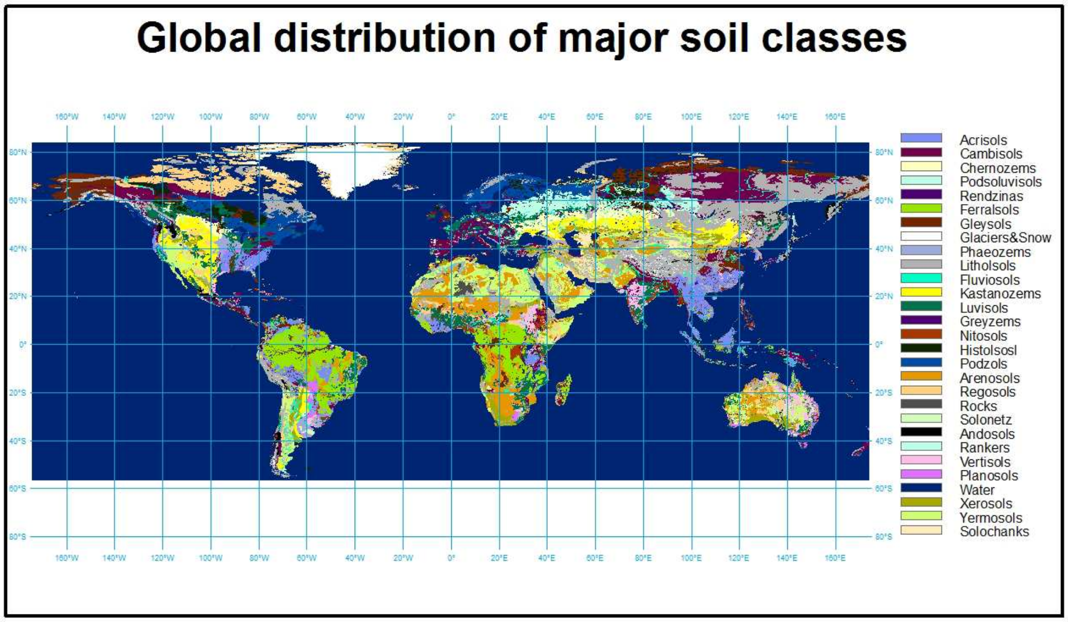

Figure 12: Global distribution of major soil classes (FOA 1974) based on the ISRIC-WISE 5‘ data

The major value of the ISRIC-WISE database consists in their derivation of 19 soil class specific chemical and physical attributes (Figure 13) relevant for crop modeling for five soil layers (0-100 cm in 20 cm increments) on a 5 arc minute resolution (N. H. Batjes 2002; N. Batjes 2006). Each 5 arc minute pixel can contain up to 8 different soil classes.

Structure of table *WISEparameterEstimates*

Name	Type	Description
CLAF	Text	FAO-Unesco (1974) Legend code
PRID	Text	profile ID (as documented in table DSMWComposition)
Drain	Text	FAO soil drainage class
Layer	Text	code for depth layer (from D1 to D5; e.g. D1 is from 0 to 20 cm)
TopDep	Integer	depth of top of layer (cm)
BotDep	Integer	depth of bottom of (cm)
CFRAG	Integer	coarse fragments (> 2mm)
SDTO	Integer	sand (mass %)
STPC	Integer	silt (mass %)
CLPC	Integer	clay (mass %)
PSCL	Text	FAO texture class
BULK	Single	bulk density (kg dm^{-3})
TAWC	Integer	available water capacity (cm m^{-1}, -33 to -1500 kPa conform to USDA standards)
CECs	Single	cation exchange capacity ($cmol_c$ kg^{-1}) for fine earth fraction
BSAT	Integer	base saturation as percentage of CECsoil
CECc	Single	CECclay, corrected for contribution of organic matter ($cmol_c$ kg^{-1})
PHAQ	Single	pH measured in water
TCEQ	Single	total carbonate equivalent (g C kg^{-1})
GYPS	Single	gypsum content (g kg^{-1})
ELCO	Single	electrical conductivity (dS m^{-1})
TOTC	Single	organic carbon content (g C kg^{-1})
TOTN	Single	total nitrogen (g kg^{-1})
CNrt	Single	C/N ratio
ECEC	Single	effective CEC ($cmol_c$ kg^{-1})

Notes:
A minus 3 indicates that no meaningful substitution was possible for the specified soil unit and attribute using the present selection of soil profiles, -1 is used for Oceans and inland waters, -2 for Glaciers and snow caps, -7 for rock outcrops (or shallow subsoils) to permit visualization using GIS.

Figure 13: Parameters considered in the ISRIC-WISE 5’ global grid from (Batjes, 2006)

This results in the ability of viewing characteristic soil parameter in a geographically explicit manner as was shown exemplary in Figure 14 for pH.

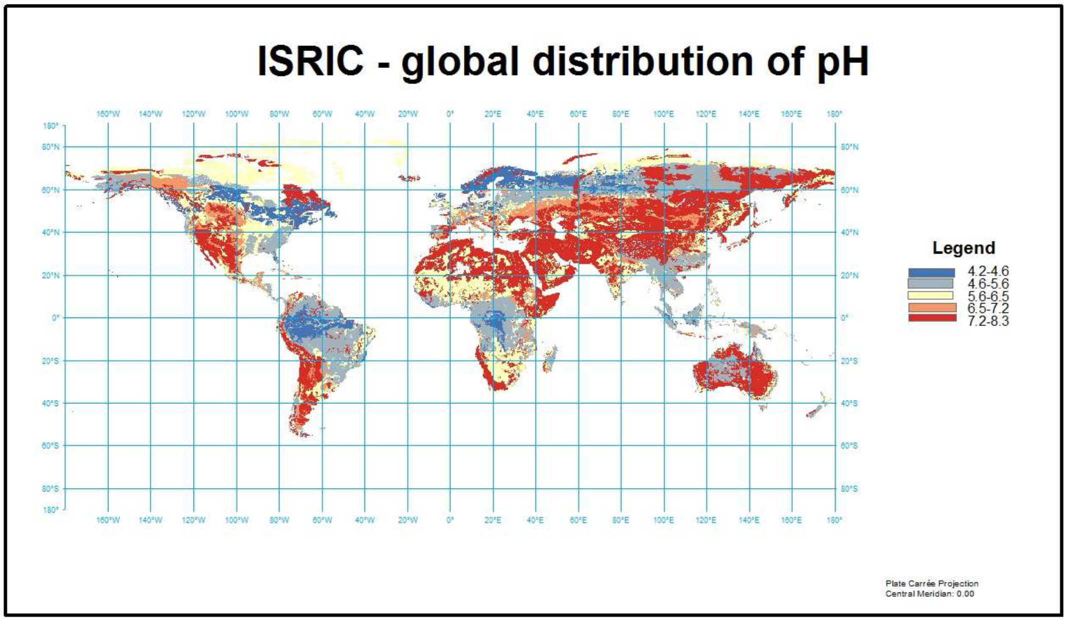

Figure 14: Distribution of acidic and basic soils on a global scale produced from ISRIC-WISE 5‘ soil data

In specific cases, such as Latin America and the Caribbean, they have developed soil maps (SOTERLAC) and according soil attributes on a 1km pixel size (Dijkshoorn 2005) where soil types are allocated based on landscape and topographical features (Figure 15), but this is not available on a global scale so far.

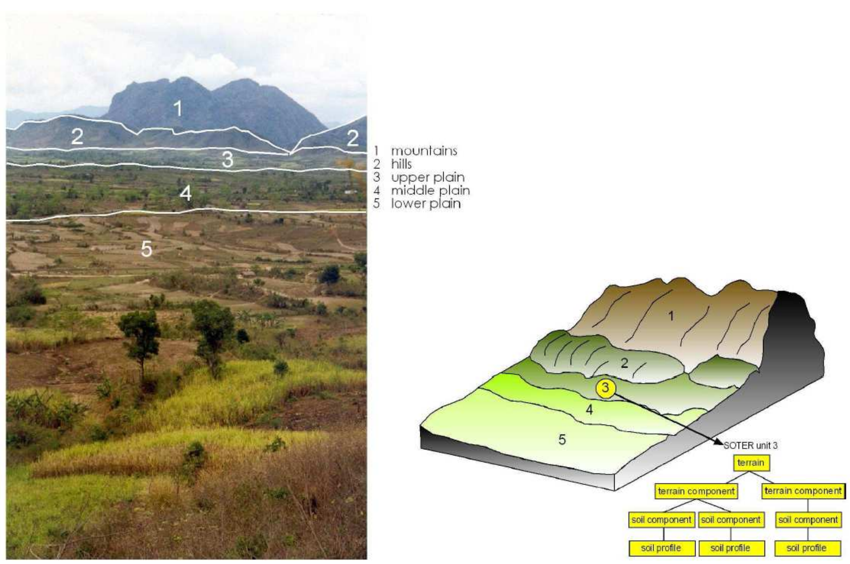

Figure 15: Schematic representation of the designation of attributes according to landscape and topography from (Dijkshoorn, 2005)

Values of the WISE database have been implemented in a variety of projects (IIASA-GAEZ, Geobene and others) and have, in some cases, been specifically adapted for the use in crop growth models as was the case for DSSAT (Gijsman, Thornton, and Hoogenboom 2007). They have however been criticized for their methodology and their lack of statistical power in terms of their assignment of parameter values based on their taxotransfer rules (Gray, Humphreys, and Deckers 2009). They further do not provide the data in our desired resolution of 30 arc second. An attempt to assign the up to 8 soil classes of the ISRIC-WISE 5by5 dataset to the 1 km pixel within each 10 km pixel by applying a negative correlation of the available water content to terrain slope (Figure 16) resulted in a rather large challenge and was not pursued any further.

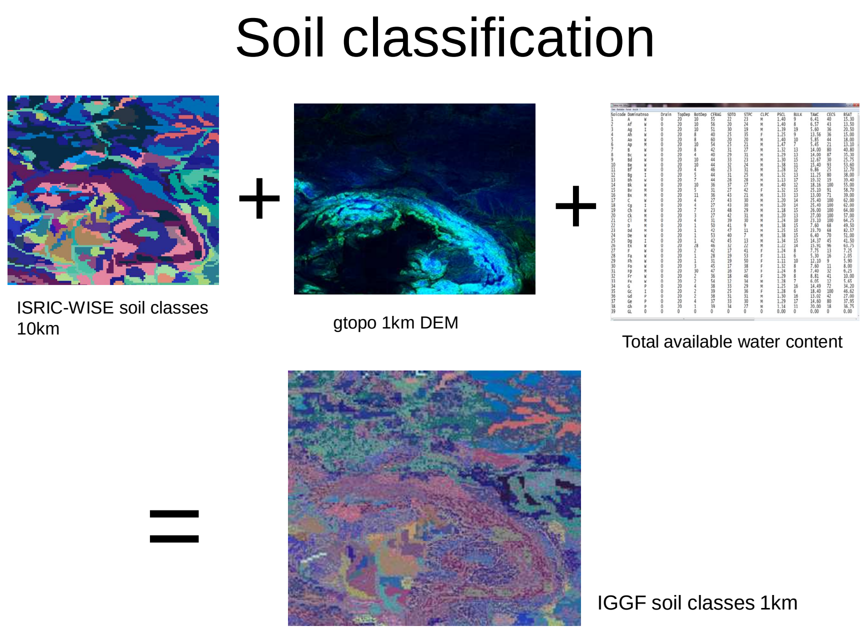

Figure 16: Methodology for assigning the soil classes of the 10km pixel to its underlying 1 km pixels.

c. Harmonized World Soil Database - HWSD

The HWSD is a joint effort of several major institutions, namely FAO, IIASA, ISRIC, Institute of Soil Science – Chinese Academy of Sciences (ISSCAS) and Joint Research Centre of the European Commission (JRC), in order to come up with a consistent global soil map at a 1km resolution integrating the most amount of spatially disaggregated information as possible while maintaining global consistency (FAO/IIASA/ISRIC/ISSCAS/JRC 2009a). This soil map was compiled in 2008 and updated in 2009 and 2012 with Version 1.2 being currently the newest. In our computations we used the 2009 version 1.1.

The HWSD contains more than 16000 soil mappings compiled from four sources: the DSMW, the ISRIC-WISE SOTER studies and the ISRIC-WISE 2.0 database, the European soil database (ESDB) and the Soil Map of China (Figure 17). Each 1km x 1km pixel can contain up to 9 different soil classes and includes 16 physico-chemical parameters as well as information on phases and other properties (Table 2) for a topsoil layer (0-30 cm) and a subsoil layer (30-100 cm). These parameters were estimated based on the WISE database using the FAO 1974 soil classification on the one hand and the FAO 1990 on the other (Annex 2: Soil classification according to FAO 1990).

Table 2: Physico-chemical information of soil properties contained in HWSD from (FAO/IIASA/ISRIC/ISSCAS/JRC 2009a)

		Field	Description	UNITS	DSMW	SOTWIS	CHINA	ESDB
Physico-chemical properties	Top Soil information	T_GRAVEL	Topsoil Gravel Content	%vol.	√	√	√	√
		T_SAND	Topsoil Sand Fraction	% wt.	√	√	√	√
		T_SILT	Topsoil Silt Fraction	% wt.	√	√	√	√
		T_CLAY	Topsoil Clay Fraction	% wt.	√	√	√	√
		T_USDA_TEX_CLASS	Topsoil USDA Texture Classification	name	√	√	√	√
		T_REF_BULK_DENSITY	Topsoil Reference Bulk Density	kg/dm3	√	√	√	√
		T_OC	Topsoil Organic Carbon	% weight	√	√	√	√
		T_PH_H2O	Topsoil pH (H2O)	-log(H^+)	√	√	√	√
		T_CEC_CLAY	Topsoil CEC (clay)	cmol/kg	√	√	√	√
		T_CEC_SOIL	Topsoil CEC (soil)	cmol/kg	√	√	√	√
		T_BS	Topsoil Base Saturation	%	√	√	√	√
		T_TEB	Topsoil TEB	cmol/kg	√	√	√	√
		T_CACO3	Topsoil Calcium Carbonate	% weight	√	√	√	√
		T_CASO4	Topsoil Gypsum	% weight	√	√	√	√
		T_ESP	Topsoil Sodicity (ESP)	%	√	√	√	√
		T_ECE	Topsoil Salinity (Elco)	dS/m	√	√	√	√

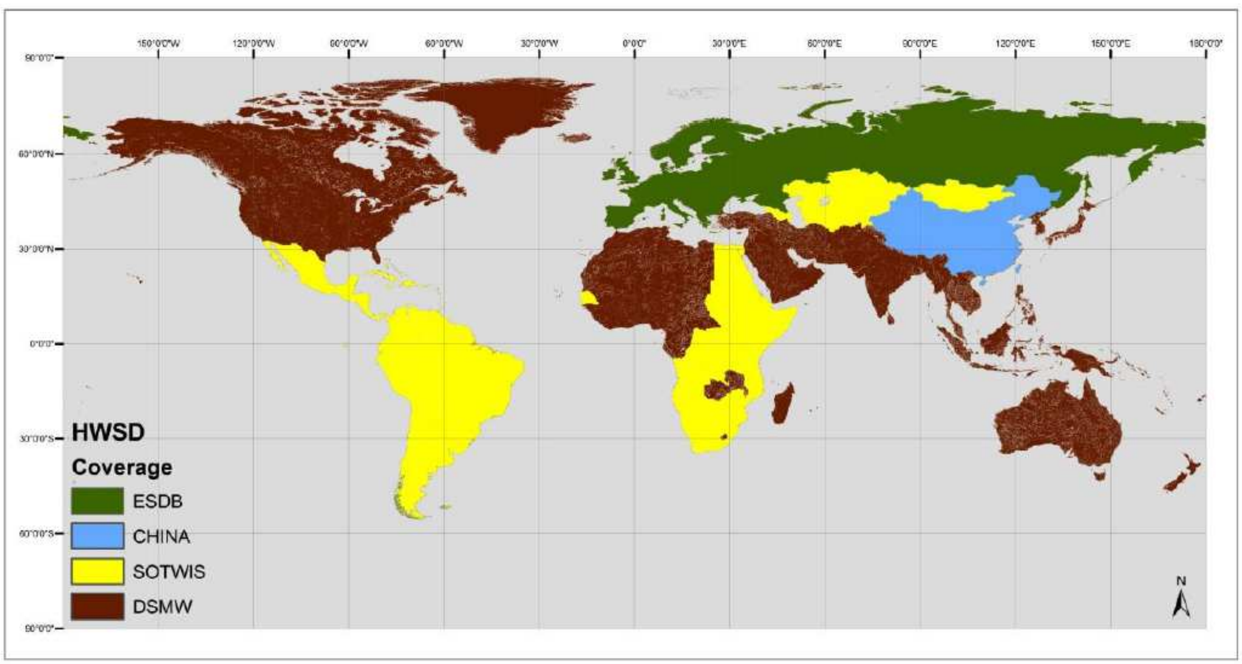

Figure 17: Geographic extent of the 4 underlying databases used for the compilation of the HWSD; European Soil Database (ESDB), Soil Map of China (CHINA), Soil and Terrain dataset (SOTWIS), Digital Soil Map of the World (DSMW); from (FAO/IIASA/ISRIC/ISSCAS/JRC 2009a)

1.2.3 Climate

a. Climate Research Unit - CRU

CRU is a Research Unit of the University of East Anglia which deals with Climate and Climate change issues. It provides a 5° dataset of monthly mean temperatures and monthly cumulative precipitation since at least 1900 based on data interpolation of roughly 3000 climate stations using HadCRUT3 and HadCRUT3v (http://www.cru.uea.ac.uk/cru/data/) (Brohan et al. 2006; Rayner et al. 2003). It is a widely used dataset in global crop suitability analysis such as the GAEZ or from SAGE (Fischer 2000; Fischer 2002; Navin Ramankutty et al. 2002) however its resolution does not fit our application.

b. European Center for Medium-Range Weather Forecasting (ECMWF)

The ECMWF is an intergovernmental organization and provides weather forecasting for its 33 supporting states (http://www.ecmwf.int/about/). They have further produced datasets of reanalyzed past forecasts with a variety of climate and atmospheric parameters in a resolution of 2,5° for the period of 1957 to 2001 in 6 hourly-time intervals (http://www.ecmwf.int/research/era/do/get/era-40) (Uppala et al. 2005). Their resolution thus does also not fit our interests.

c. WorldClim

WorldClim is a joint effort between the Museum of Vertebrate Zoology of the University of California, Berkley, the International Center for Tropical Agriculture and the Cooperative Research Center for Tropical Rainforest Ecology and Management. The dataset consists of mean monthly temperature, minimum monthly temperature, maximum monthly temperature, cumulative monthly precipitation and bioclimatic variables in four different resolutions (30 arc sec, 2.5', 5' and 10') (http://www.worldclim.org/). The data was derived from interpolation between 15000 to 47000 weather stations globally in the time period from 1950 to 2000 (Hijmans et al. 2005). We decided to use this dataset for our historic crop suitability analysis.

d. Kiel Climate Model (KCM) of the Leibniz Institute for Marine Science at the University Kiel

The KCM is a global climate model which is used to predict climate from interannual to millennial time scales (Park et al. 2009) with a resolution of 3,75° (atmospheric resolution T31). We were initially thought to be provided with three datasets (1960-1990, 2030-2040, 2070-2100) in hourly time steps for several parameters, including 2m temperature and precipitation. Future climate was predicted under the A1B IPCC scenario (IPCC 2007). A downscaling process was performed as described in (Marke et al. 2011). In the end, we received the climate information form ECHAM 5, from the Max-Planck Institute in Hamburg (see (Roeckner et al. 2003) for further information on ECHAM 5).

e. General Circulation Models (ECHAM, HadMC, etc)

General Circulation Models started being developed in the 1950's based on general properties of the atmosphere. Traditional Atmosphere-Ocean Models are produced by NOAA's Geophysical Fluid Dynamics Laboratory, the US National Center for Atmospheric Research, the Hadley Centre for Climate Prediction and Research and the Max Planck Institute for Meteorology, among others. Based on Numerical Weather Prediction methods the ECHAM series forms the atmospheric component of the Earth System Model of the Institute (MPI-ESM).

1.2.4 Landcover/ Landuse

a. GlobCover

GlobCover is a European Space Agency (ESA) initiative to produce global composites of the 300 m MERIS observation on board the ENVISAT satellite mission. The data is available since 2005 and three sets of data can be obtained either as bimonthly Normalized Difference Vegetation Index (NDVI) composites in tiles of 5° x 5° for the periods of November 2004-June 2006 and January 2009-December 2009, or as yearly composites of the year 2005 and 2009, or as land cover maps for the given years using the FAO LCCS (Figure 18, Annex 3: Globcover classification legend) (http://ionia1.esrin.esa.int/). A comparison between the two time sets is tempting, i.e. to see changes in land cover, but not advisable as methodologies have been updated since the first set of results (Bontemps et al. 2009).

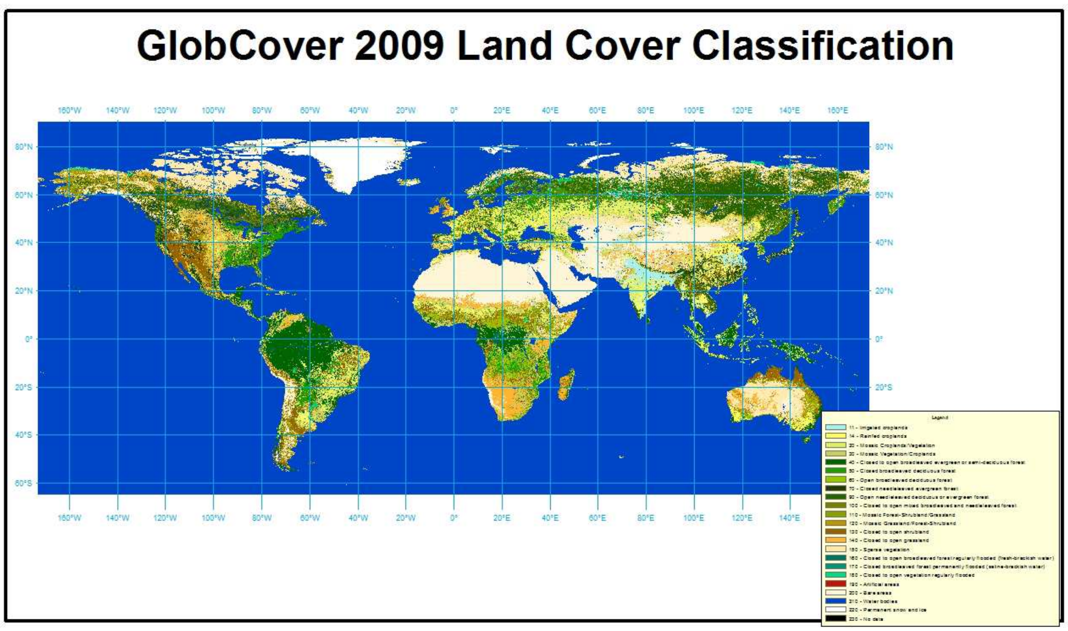

Figure 18: GlobCover 2009 Land Cover Classification

b. Urban areas

(Schneider, Friedl, and Potere 2010) produced a dataset of the geographic extent and placement of urban areas on a 500 m resolution based on MODIS data. They define urban areas as 'contiguous patches of built-up land greater than 1 km^2' (Schneider, Friedl, and Potere 2009) and divided the world into 'urban ecoregions' by ecological, economic and socio-historic differences (Figure 19).

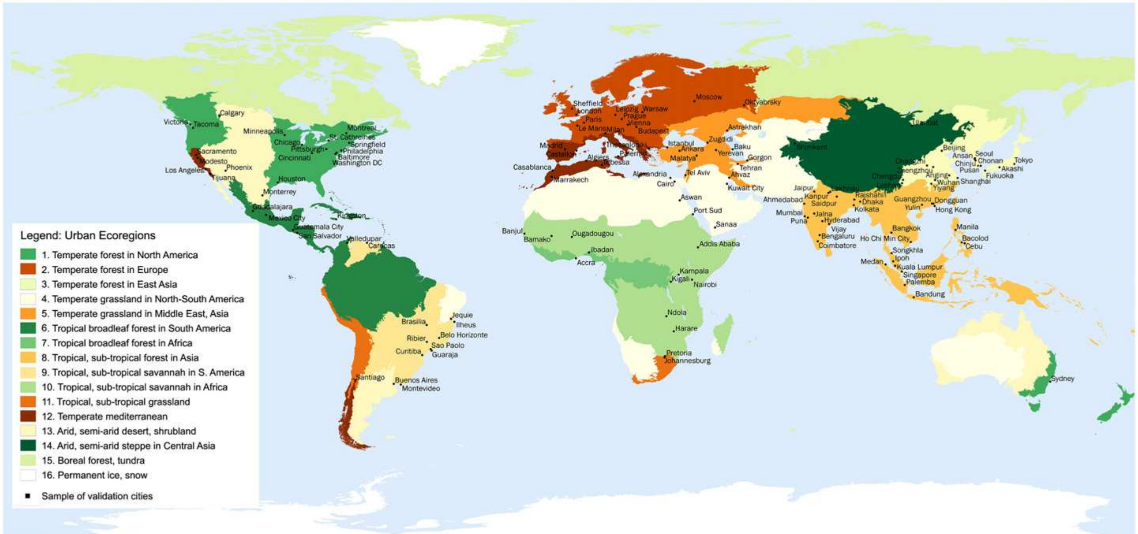

Figure 19: Delineation of urban ecoregions as defined by (Schneider et al., 2010)

In comparison with Landsat images of 140 cities of these ecoregions they achieved an accuracy of 93% (Schneider et al., 2010) making this one of the most accurate urban land maps currently available (Figure 20).

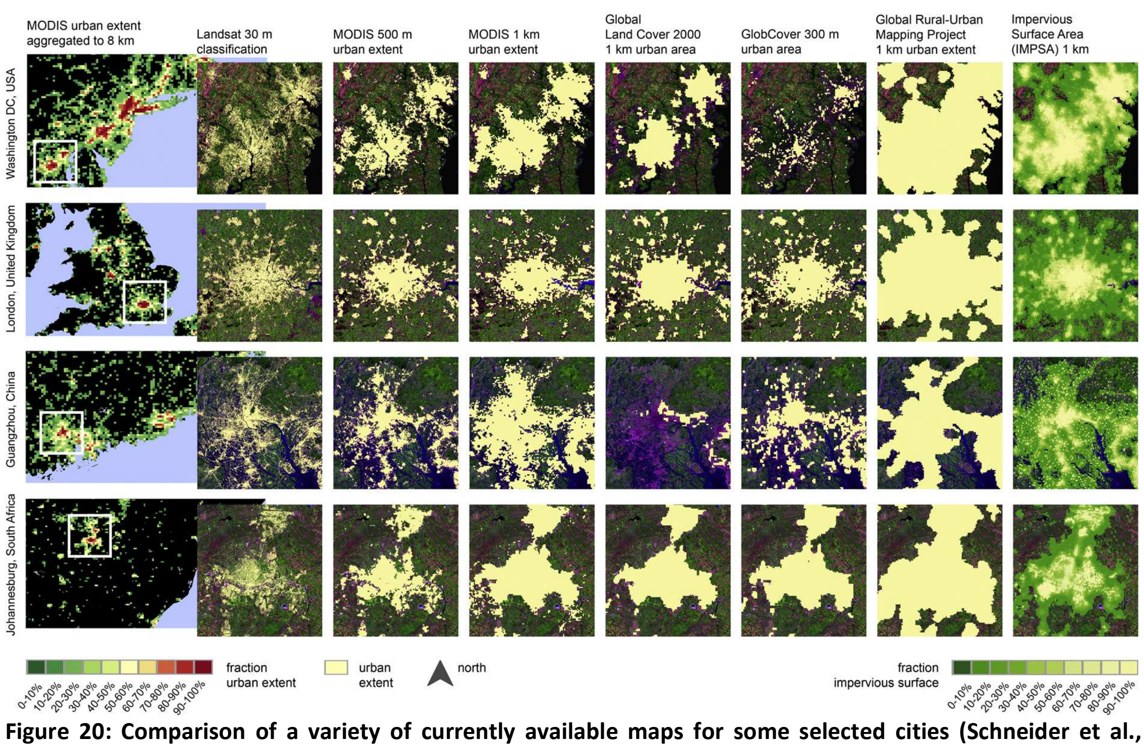

Figure 20: Comparison of a variety of currently available maps for some selected cities (Schneider et al., 2010)

c. IUCN protected areas

The IUCN, the International Union for Conservation of Nature, has integrated the protected areas of the world into a database and map system (IUCN and UNEP 2010; IUCN 2010). They distinguish between six following categories according to the guidelines set forth in the 1994 IUCN guidelines (Dudley 2008):

Areas managed mainly for:	
I	Strict protection [Ia) Strict nature reserve and Ib) Wilderness area]
II	Ecosystem conservation and protection (i.e., National park)
III	Conservation of natural features (i.e., Natural monument)
IV	Conservation through active management (i.e., Habitat/species management area)
V	Landscape/seascape conservation and recreation (i.e., Protected landscape/seascape)
VI	Sustainable use of natural resources (i.e., Managed resource protected area)

Extent of the areas can be accessed via (IUCN and UNEP, 2010).

d. Actual harvested areas in the year 2000

The researchers at SAGE (Center for Sustainability and the Global Environment at the University of Madison, Wisconsin) used remote sensing data and coupled it to national or sub-national harvest information into homogenous subsets of soil-climate-terrain areas to produce maps of actual extent of harvested areas (N. Ramankutty et al. 2008; Monfreda, Ramankutty, and Foley 2008).

Through the integration of remote sensing data, in particular from Advanced Very High Resolution Radiometer (AVHRR) and later based on MODIS and SPOT VEGETATION, with crop statistics - FAOSTAT and AgroMAPS - SAGE has been able to produce global maps of land cover and crop distributions (Figure 21) (N. Ramankutty et al. 2008; N. Ramankutty 1998). The climatic input data is derived from the CRU05 climate dataset from the University of East Anglia with mean monthly climate conditions from 1961-1990 in a 0.5° grid. The soil moisture parameters are obtained from the Global Soils Data Task Group of the International Geosphere-Biosphere Programme (Loveland and Belward 1998) at a 5’ resolution.

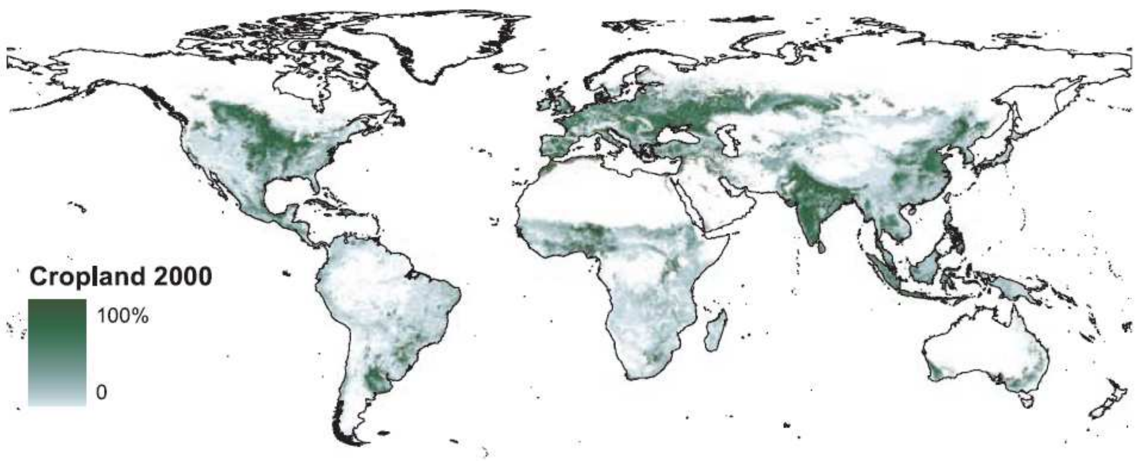

Figure 21: Distribution of croplands in the year 2000 after (Ramankutty et al., 2008)

Overview of the publications

This thesis summarizes the following three publications:

- Avellan, T., Zabel, F., & Mauser, W. (2012). The influence of input data quality in determining areas suitable for crop growth at the global scale – a comparative analysis of two soil and climate datasets. Soil Use and Management, 28(2), 249–265. doi:10.1111/j.1475-2743.2012.00400.x
- Avellan, T., F. Zabel, B. Putzenlechner, and W. Mauser. 2013. "A Comparison of Using Dominant Soil and Weighted Average of the Component Soils in Determining Global Crop Growth Suitability." Environment and Pollution 2 (3) (May 29). doi:10.5539/ep.v2n3p40. http://www.ccsenet.org/journal/index.php/ep/article/view/27860.
- Avellan, T., Meier, J., & Mauser, W. (2012). Are urban areas endangering the availability of rainfed crop suitable land? Remote Sensing Letters, 3(7), 631–638. doi:10.1080/01431161.2012.659353

The first paper is a comprehensive analysis of two of the previously described sets of global databases: soil and climate. It also analyses the effect of these datasets on crop suitability. Two Bachelor theses served as the basic analyses for the dataset comparison (see Hartmann 2011 and Günther 2011). We modeled the crop suitability output of the combination of two climate datasets and two soil datasets using three spatial resolutions.

The second paper, analyses one aspect of the complexity of soil databases more in depth. Soil databases offer a variety of parameters sampled and compiled in many ways. In our previous model runs we had only used the dominant soil parameter value estimate of the topsoil. Here, we look at the effect on crop suitability while using all component soils (up to 9) of the HWSD.

The third paper builds on the most precise modeling output of the first paper and addresses the question of urban areas in competition to crop suitable areas. Using the urban areas dataset of Schneider et al. described above we looked at the placement of cities in respect to crop suitable areas. Three Bachelor theses looked at the regional effect of urban areas on crop suitable areas and served as the basis of the discussion on the effect of the expansion of cities on agricultural food production (see Nitsch 2011, Haun 2011 and Meier 2011).

Below you can find the abstracts of each of the publications for further insight.

1.3 Overview of the publications

1.3.1 The influence of input data quality in determining areas suitable for crop growth at the global scale – a comparative analysis of two soil and climate datasets.

The assessment of biophysical crop suitability requires datasets on soil and climate. In this study, we investigated the differences in topsoil properties for the dominant soil mapping units between two global soil datasets. We compared the ISRIC World Soil Information Center' s World Inventory of Soil Emissions Potential 5 by 5 arc min Soil Map of the World (ISRIC-WISE 5by5 SMW) with the Harmonized World Soil Database (HWSD) in 0.5 arc min. We also incorporated annual mean temperature and mean precipitation from two global climate datasets that were the WorldClim measurement-based climate dataset and the Kiel Climate Model (KCM)[1] modelled results of global climate from 1960 to 1990. We then applied a fuzzy logic approach using different combinations and resolutions of the datasets to determine the effects on the extent and distribution of suitable areas for 15 crops. We only used the spatially dominant soil class in the mapping units in the soil databases (resampled to the same resolution of 5 arc min), and we found that the estimates of topsoil properties (0–20 cm in ISRIC-WISE and 0–30 cm in HWSD) of the seven analysed parameters were up to 40% lower in most of the HWSD than in the ISRIC-WISE 5by5 SMW. Results from the KCM are 0.1 °C (1%) lower in mean global annual temperature and 20% higher in average global annual precipitation compared with the WorldClim data. The HWSD-based runs resulted in 10% less crop-suitable land than the ISRIC-WISE 5by5 SMW-based results. The KCM simulations predicted 1% less crop-suitable land than the WorldClim model. Despite generalizations, our results demonstrate that discrepancies in crop suitable areas are largely due to the differences in the soil databases rather than to climate.

1.3.2 A comparison of using dominant soil and weighted average of the component soils in determining global crop growth suitability

Soil parameters represent key data input for crop suitability analysis. Soil databases are complex offering soil mapping units made up of various component soils. In the case of the Harmonized World Soil Database there can be up to 8 component soils per unit. In roughly 1/3 of soil mapping units, the additional component soils take up more than 50 % of the pixel share value. The soil parameter value estimate, such as pH, salinity and organic carbon content, may differ between the value of the dominant soil component and the weighted average of the values of all component soil. Understanding the effect of these differences on crop model outputs may allow quantifying the

[1] We actually used ECHAM5 modelling results. But at the time of the publication we were not aware of this.

error. In this study, we show the changes in crop suitability of 15 crops while using the parameter value estimates of the dominant soils versus a weighted average of the component soils. In the case of the latter, global crop suitability amounts to 54.5% of the earth's land surface - 1 % more than when using the values of just dominant soils. Intrinsic regional differences in the quality of the soil database influence the distribution of crop suitability classes especially in areas where share values of the dominant soil are low. The uncertainty range for the use of dominant versus component soils on the overall global crop suitability could be considered to be 1 %, while that of each suitability class can amount to up to 4 %.

1.3.3 Are urban areas endangering the availability of rainfed crop suitable land?

Many concerns have been raised about urban sprawl and the subsequent disappearance of agricultural land. Regulations have been put in place to reduce urban sprawl and protect agricultural areas in many countries, but how much potentially crop suitable land really is endangered by urban areas on a global scale has not been addressed so far. In this study, we compare the extent of urban areas as produced by the Center for Sustainability and the Global Environment, Madison, WI, USA, with a map of potential crop suitable areas produced by us. We show that, of the postulated 0.5% of the Earth's surface currently covered by urban areas, Asia, Europe and North America take away the largest shares and that 1% of the globally available highly crop suitable areas are currently taken up by cities, with Japan and California being extreme examples of up to 15% of highly suitable areas covered with cities.

Conclusions and Outlook

This thesis provided a successful attempt of undertaking an analysis of the crop suitable areas of the 15 most relevant crops at the global scale using a spatial resolution of roughly 1 km at the equator. The methodology that was chosen relied on fuzzy logic and based itself on standard crop growth parameters as recommended by FAO. Overall, roughly half of the globe's land surface (excluding Antarctica) is suitable for some sort of crop growth with the current high production sites being generally the most suitable ones. Comparison with the datasets by Ramankutty et al., for instance, showed that historic crop areas coincide in more than 70% of the pixel with our simulations.

The careful analysis of the underlying biophysical databases – terrain, soil and climate – showed that inconsistencies were largest amongst the soil datasets and smallest in the climate and terrain datasets. In depth studies of the complexity of the soil databases unveiled a variety of sources that may influence crop growth suitability – one of them being the number of component soils used for the computation of soil parameter value estimates.

The complexity of the interplay between underlying parameters, number and type of crops that are being simulated, their varying abilities to grow under diverse bio-physical conditions and modeling challenges themselves make this study highly useful. Unlike other, similar studies this thesis has tried to estimate some of the errors and error rates that occur while simulating crop suitable areas. The use of dominant soil parameter value estimates versus all component soils, for instance, may account for roughly 1 % of the overall differences.

Analyzing the global distribution of crops and how they related to urban areas, protected areas and other land uses is a worthwhile exercise. We were able to show that 1% of all crop suitable areas have already fallen victim to urban sprawl, whilst 12% of the protected areas are suitable for crop growth. Special care has to be taken where urban areas expand into, in order to prevent further deterioration and laws need to be further enforced to maintain the protected areas intact in order to prevent further land conversions.

Land conversions are most profitable in South America and Sub-Saharan Africa where potentially crop suitable areas still prevail. One must keep in mind, however, that this study analyses purely the biophysical conditions which presents certain limitations. Hence, areas such as the Nile Delta for instance, that rely heavily on irrigation, do not appear suitable for crop growth in our results. Use of fertilizer, pesticides, selected crops and use of machinery allows for an increase in production and an expansion of cropping areas beyond the ones shown here. On the other hand, one must also keep in mind that soil datasets are based on samples taken in the 1960’s and 1970’s. Soil composition may have strongly changed in the mean time through erosion but also through heavy fertilization processes.

The studies here also present severe limitations in the temporal resolution of the climate dataset. Using the annual mean temperature and the annual cumulative rainfall over a 30 year average is hardly representative of day to day crop necessities. Crops usually fail due to the lack of rainfall at critical phenological stages or due to periods of excessive cold or heat. In a subsequent step to the result presented here, the team at LMU refined the model further in order to include daily climate inputs. This also allowed for crops to ‘select’ their best day to start their growing cycle by assigning certain thresholds of temperature and water availability. Further refinements were also undertaken in terms of the exclusion and inclusion of certain areas such as regions under permafrost and irrigated areas. These methods and refinements will hopefully also be published shortly.

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Appendix

Soil Use and Management

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The influence of input data quality in determining areas suitable for crop growth at the global scale – a comparative analysis of two soil and climate datasets

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Abstract

The assessment of biophysical crop suitability requires datasets on soil and climate. In this study, we investigated the differences in topsoil properties for the dominant soil mapping units between two global soil datasets. We compared the ISRIC World Soil Information Center's World Inventory of Soil Emissions Potential 5 by 5 arc min Soil Map of the World (ISRIC-WISE 5by5 SMW) with the Harmonized World Soil Database (HWSD) in 0.5 arc min. We also incorporated annual mean temperature and mean precipitation from two global climate datasets that were the WorldClim measurement-based climate dataset and the Kiel Climate Model (KCM) modelled results of global climate from 1960 to 1990. We then applied a fuzzy logic approach using different combinations and resolutions of the datasets to determine the effects on the extent and distribution of suitable areas for 15 crops. We only used the spatially dominant soil class in the mapping units in the soil databases (resampled to the same resolution of 5 arc min), and we found that the estimates of topsoil properties (0–20 cm in ISRIC-WISE and 0–30 cm in HWSD) of the seven analysed parameters were up to 40% lower in most of the HWSD than in the ISRIC-WISE 5by5 SMW. Results from the KCM are 0.1 LC (1%) lower in mean global annual temperature and 20% higher in average global annual precipitation compared with the WorldClim data. The HWSD-based runs resulted in 10% less crop-suitable land than the ISRIC-WISE 5by5 SMW-based results. The KCM simulations predicted 1% less crop-suitable land than the WorldClim model. Despite generalizations, our results demonstrate that discrepancies in crop suitable areas are largely due to the differences in the soil databases rather than to climate.

Keywords: Crop suitability, HWSD, ISRIC-WISE, WorldClim, grid size resolution

Introduction

An increase in food production is essential for the world's population that is expected to rise to 8.3 billion by 2030 (UNPD, 2009). The need for enhanced production has become more acute because of the shift from basic food crops to oil crops for biofuels and fodder for livestock (Foresight, 2011). Data on potential yield for different areas and crops are needed to plan for a steady and secure production of food and industrial crops at affordable prices.

An analysis of potential crop yield is usually preceded by the determination of crop-suitable land, and this has been done in a few studies at a global scale (Fischer et al., 2000, 2002; Monfreda et al., 2008; Ramankutty et al., 2008). Land capability is the inherent capacity of land to perform at a given level for general use (FAO, 1976). Land suitability is fitness for a defined use. The FAO (1976) 'Framework for land evaluation' is based on five suitability classes (Table 1), three being suitable for agricultural production and two being unsuitable (FAO, 1976). Crucial to crops are soil quality and climate. The quality of soil determines the kind of vegetation that can optimally grow. Climate dictates average available sunlight, overall energy and water for plant growth (Andreae, 1983; Grigg, 1995). Sys et al. (1993) provide detailed growing requirements for specific crops, and these have been used in several crop suitability studies (e.g. Kalogirou, 2001; Baja et al., 2002; Fischer et al., 2002). However, these requirements are the result of global studies and do not

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Table 1 Suitability classification according to FAO 1976

Class S1 Highly Suitable	Land having no significant limitations to sustained application of a given use, or only minor limitations that will not significantly reduce productivity or benefits and will not raise inputs above an acceptable level
Class S2 Moderately Suitable	Land having limitations that in aggregate are moderately severe for sustained application of a given use; the limitations will reduce productivity or benefits and increase required inputs to the extent that the overall advantage to be gained from the use, although still attractive, will be appreciably inferior to that expected on Class S1 land.
Class S3 Marginally Suitable	Land having limitations that in aggregate are severe for sustained application of a given use and will so reduce productivity or benefits or increase required inputs that this expenditure will be only marginally justified
Class N1 Currently Not Suitable	Land having limitations that may be surmountable in time but cannot be corrected with existing knowledge at currently acceptable cost; the limitations are so severe as to preclude successful sustained use of the land in the given manner
Class N2 Permanently Not Suitable	Land having limitations that appear so severe as to preclude any possibilities of successful sustained use of the land in the given manner

reflect other complex issues such as site-specific cultivars or local management practices.

Digital maps at the global scale of soil quality parameters are few and vary in quality (Gijsman et al., 2007; Batjes, 2009; FAO, IIASA, ISRIC, ISS-CAS & JRC, 2009; Gray et al., 2009; Nachtergaele et al., 2009). Most countries have published soil maps, albeit often using different standards with diverse soil classes (Batjes, 2002a; FAO, 2006) and classification schemes (FAO, IIASA, ISRIC, ISS-CAS & JRC, 2009). Historically unified global soil classifications have been a focus for FAO in establishing standardized soil class characteristics with revisions in 1974, 1985, 1990/92 (FAO & UNESCO, 1997; FAO, 1998; FAO, 2006). The first integrated soil map for the world was produced in the 1970s with the 'Soil Map of the World,' later digitized in the 'Digital Soil Map of the World' (DSMW) (FAO, 1995; FAO & UNESCO, 1997). To undertake ecological modelling, we need information contained in the soil classes – namely parameters such as pH, organic carbon and salinity (Batjes, 2002b). Two examples of projects using such properties are

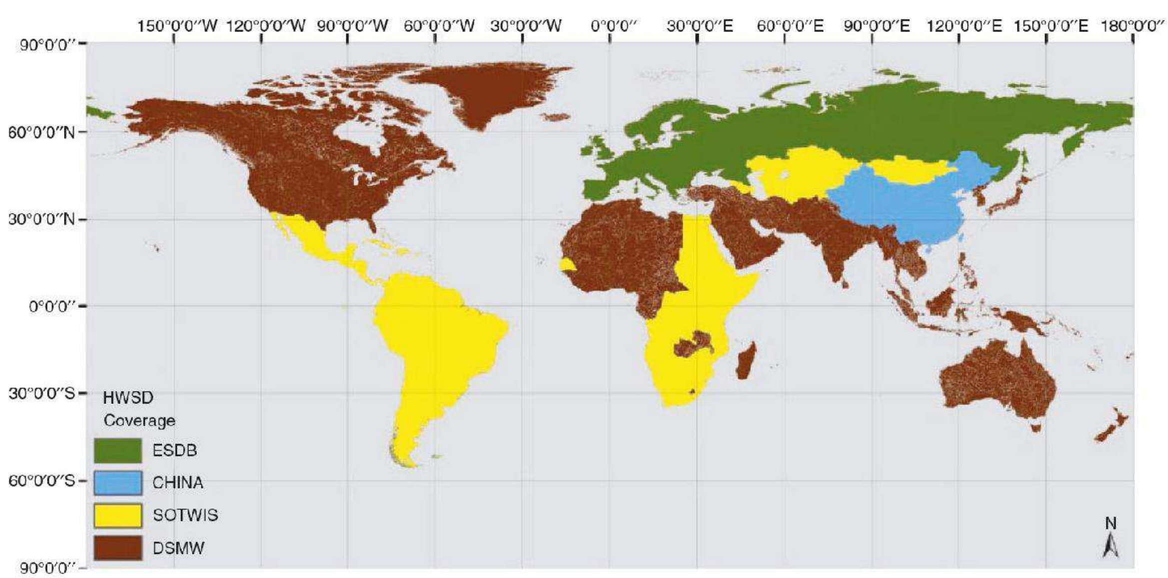

Figure 1 Geographic extent of the four underlying databases used for the compilation of the harmonized world soil database (HWSD); European Soil Database (ESDB), Soil Map of China (CHINA), Soil and Terrain dataset (SOTWIS), Digital Soil Map of the World; from (FAO, IIASA, ISRIC, ISS-CAS & JRC, 2009).

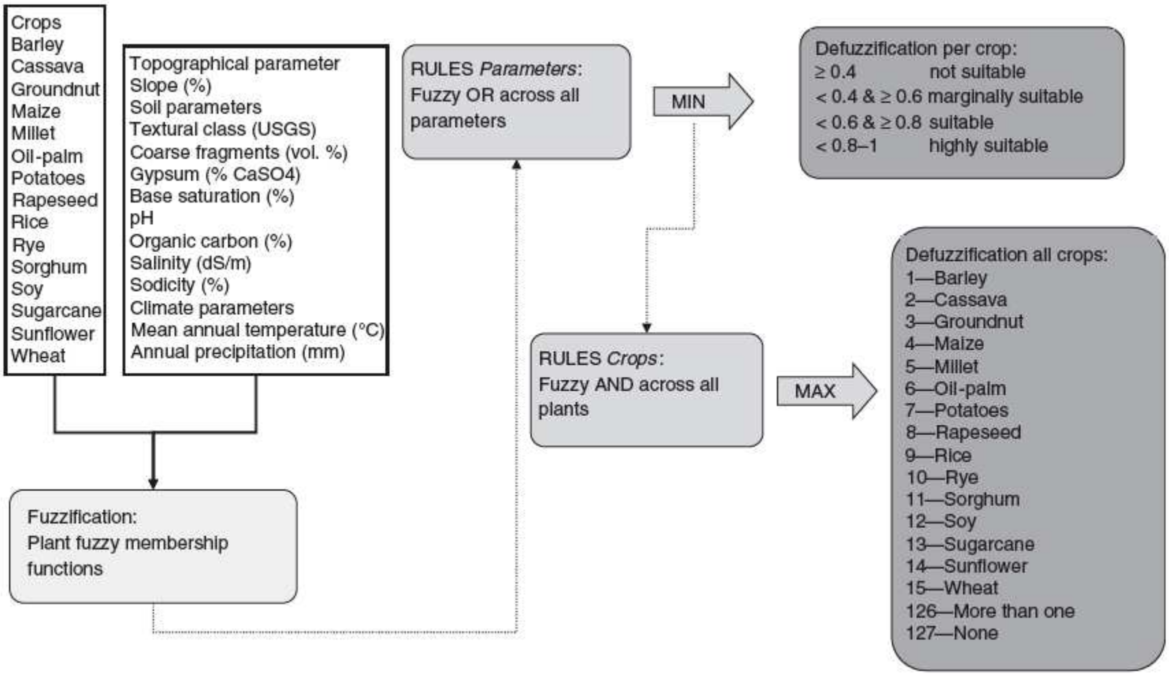

Figure 2 Methodology of fuzzy logic determination of crop-suitable areas for each of the 15 plants (MIN) and for the most suitable plant (MAX).

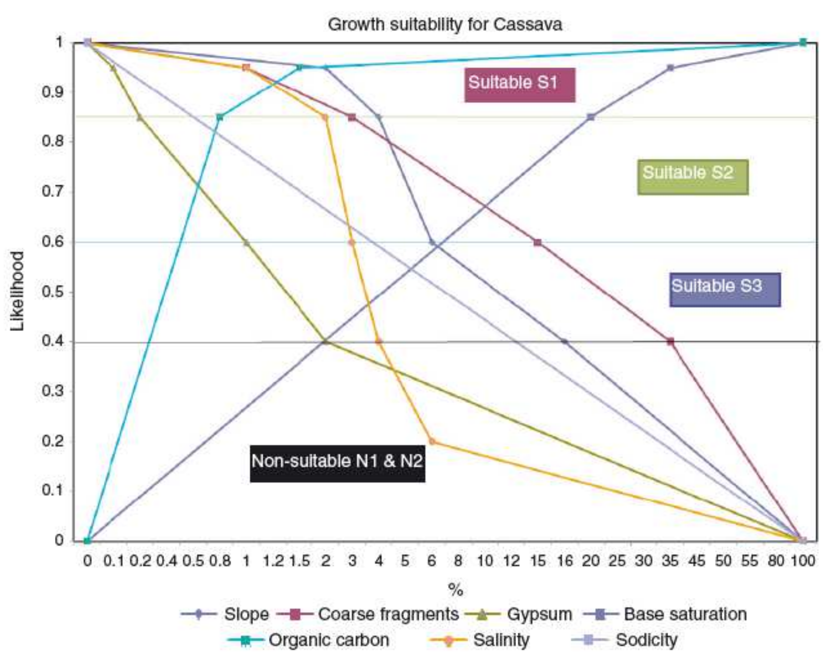

Figure 3 Examples of membership functions and corresponding suitability thresholds for some selected parameters for Cassava based on the growth parameter values of Sys et al. (1993). At each selected pixel the value for each parameter is determined (fuzzy OR rules) and the minimum likelihood of each value is assigned for this plant (defuzzification per crop). This minimum likelihood is then compared across all crops (fuzzy AND rules) and the maximum across all crops is assigned to this pixel (defuzzification across all crops), thus identifying the most suitable crop for that pixel and its suitability level.

(i) the ISRIC-WISE database and their Soil Map of the World (ISRIC-WISE 5by5 SMW) (ISRIC, 2005) and (ii) the Harmonized World Soil Database (HWSD) (FAO, IIASA, ISRIC, ISS-CAS & JRC, 2009). The approach of the ISRIC-WISE 5by5 SMW is based on the harmonization of global soil information. It relies on the extent of soil mapping units of the DSMW coded in the FAO 1974 classification at a 5-arc min resolution (Batjes, 2006). Taxonomy-based pedo-transfer functions combined with expert rules were applied to provide estimates of 19 soil parameters relevant to global agro-ecological modelling (Batjes, 2006). The HWSD project used a compilation of four regional soil databases of variable quality and soil mapping unit extent (European Soil Database, Soil Map of China, regional SOTER datasets and DSMW) (Figure 1) and integrated these on a 30 arc s resolution (FAO, IIASA, ISRIC, ISS-CAS & JRC, 2009). Similar techniques to the ISRIC-WISE datasets were applied except that soil classes were defined by either the FAO (1974) or the FAO (1990) systems.

Table 2 Overview on the combination of datasets used in the simulation using all constraints

		0.5635°			
Resolution	Dataset	KCM	WC	0.083°WC	0.0083°WC
0.5635°	HWSD	x	x		
	ISRIC	x	x		
0.083°	HWSD			x	
	ISRIC			x	
0.0083°	HWSD				x

Historic global maps of climatic characteristics exist (Hijmans et al., 2005; Uppala et al., 2005), and there are a plethora of future simulations (IPCC, 2007a,b). Several thousand weather stations exist worldwide, but these are prone to measurement errors and have not always provided continuous datasets. Error rates for temperature are +∕- 0.1 °C in Europe whereas these can be up to 50% for precipitation and 100% for snow, especially in mountainous areas (Scho¨nwiese, 2008). To our knowledge, there are currently two global datasets that rely on historic data (1959–1990) from weather stations, namely the CRU data at a 0.5 arc degree resolution (CRU, 2011) and the WorldClim dataset at 30 arc s (UC Berkley et al., 2005). Other ways of obtaining climatic parameters include the re-analysis of weather predictions such as the ERA data (Uppala et al., 2005) or the use of climate models (IPCC, 2007a). Results from climatic models are expressed at different spatial and temporal resolutions (Roeckner et al., 2004; IPCC, 2007a; Zabel et al., 2011). However, climate models are currently our only way of assessing future

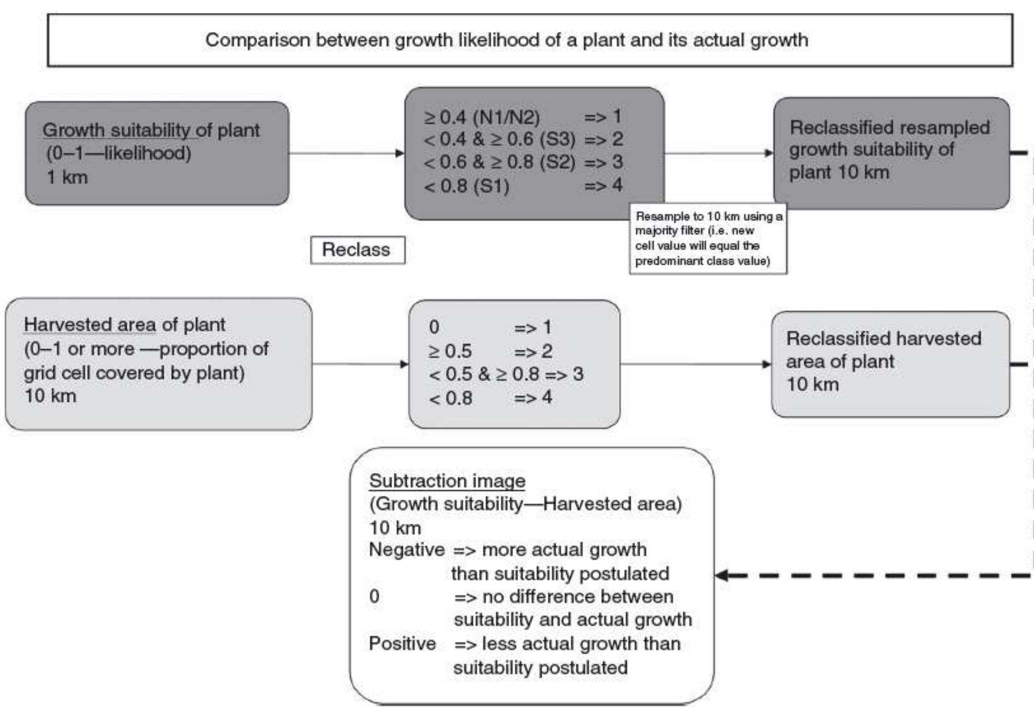

Figure 4 Methodology for comparing the extent of suitable areas and the actual harvested area (Ramankutty et al., 2008).

changes in the two key plant growth criteria – temperature and precipitation.

Often soil and climatic parameters exhibit inherent errors and of course crops grow across a range of conditions. The use of strict Boolean classification systems is too restrictive in growth ranges to define crop suitable areas at the global scale. Burrough et al. (1992) and Rossiter (1996) use fuzzy classification methods as a solution. Local to regional crop suitability studies using fuzzy logic are available (Van Ranst et al., 1996; Ahamed et al., 2000; Baja et al., 2002; Braimoh et al., 2004; Kurtener et al., 2008), but not at the global scale.

Our aim was to investigate the effect of using different datasets in predicting the potential extent of 15 crops. We first analysed differences between the two global soil datasets ISRIC-WISE 5by5 SMW and HWSD as well as between the WorldClim and Kiel Climate Model climate datasets for 1960– 1990. Then, we analysed the extent and distribution of crop suitability using different combinations of the datasets.

Materials and methods

Global datasets. All analyses were carried out for the earth’s land surface excluding Antarctica using eight soil properties as recommended by Sys et al. (1993): textural class (USGS), coarse fragments (volume %), gypsum (% $CaSO_4$), base saturation (%), pH, organic carbon (%), salinity (dS ⁄ m) and sodicity (%). Two datasets were used, (i) the Harmonized World Soil Database (HWSD) (FAO, IIASA, ISRIC, ISS-CAS & JRC, 2009) and (ii) the ISRIC-WISE 5by5 SMW (referred to as ISRIC) (Batjes, 2006). We used topsoil property values as estimated for the spatially dominant soil in each mapping unit neglecting spatial variation in soil unit types as originally mapped (i.e. up to eight component soils per mapping unit) (Batjes, 2006; FAO, IIASA, ISRIC, ISS-CAS & JRC, 2009). Topsoil depths differ, ISRIC deals with 0–20 cm whilst HWSD extends to 30 cm and we did not consider subsoil estimates. Each database based the estimation of soil values on differing numbers of soil profiles and on different regional samples (Nachtergaele et al., 2009). We used annual mean temperature and annual cumulative precipitation from two climate datasets from 1960–1990. WorldClim in 30 arc s (1 · 1 km at the equator) integrates and interpolates climatic information from weather stations (Hijmans et al., 2005). The Kiel Climate Model (KCM) in 34 arc min (67 · 67 km at the equator) (Park et al., 2009) is a global climate model and has been used to predict climate for interannual to millennial timescales (Park et al., 2009). The slope was computed as per cent rise from a global digital elevation model, the SRTM30 DEM (Farr et al., 2007) (USGS, 2000).

Comparison of datasets of the same type. Datasets were resampled at lower resolutions as necessary using a majority filter for classified parameters and bilinear

Table 3 Global mean signed differences in topsoil parameter estimates for the spatially dominant soil units of the corresponding mapping units between the WISE and the HWSD, Harmonized World Soil Database (HWSD) soil databases. Results are given for the globe and for three regional examples. Difference = HWSD values) WISE values. % Difference = [(HWSD value) WISE value) ⁄ WISE value] · 100

	Global				China			
	WISE	HWSD	Difference	% Difference	WISE	HWSD	Difference	% Difference
Coarse fragments (vol. %)	11.2	8.4	−2.8	−25.1	15.8	8.9	−7.0	−44.1
Gypsum (%)	8.3	8.5	0.1	1.4	19.0	19.4	0.4	2.0
Base saturation (%)	76.2	71.7	−4.5	−5.9	90.3	83.0	−7.2	−8.0
pH	6.4	6.2	−0.2	−2.4	7.0	6.6	−0.4	−6.1
Organic Carbon (%)	2.2	2.2	0.0	0.3	1.4	1.1	−0.3	−18.3
Salinity (dS/m)	0.6	0.3	−0.2	−42.7	1.3	0.8	−0.6	−42.6
Sodicity (%)	3.4	2.4	−1.0	−30.5	4.3	2.5	−1.7	−40.8
	Brazil				USA			
Coarse fragments (vol. %)	4.8	7.0	2.1	43.5	7.0	9.0	2.0	29.1
Gypsum (%)	1.9	0.6	−1.3	−68.6	1.7	1.2	−0.5	−27.5
Base saturation (%)	35.8	29.8	−6.0	−16.8	76.9	78.3	1.4	1.8
pH	5.2	4.9	−0.3	−5.4	6.4	6.4	0.0	−0.3
Organic Carbon (%)	1.2	1.2	0.0	4.0	1.4	1.4	0.0	0.8
Salinity (dS/m)	0.1	0.0	−0.1	−91.4	0.3	0.2	−0.1	−26.9
Sodicity (%)	3.0	0.9	−2.1	−68.6	2.6	2.2	−0.4	−14.7

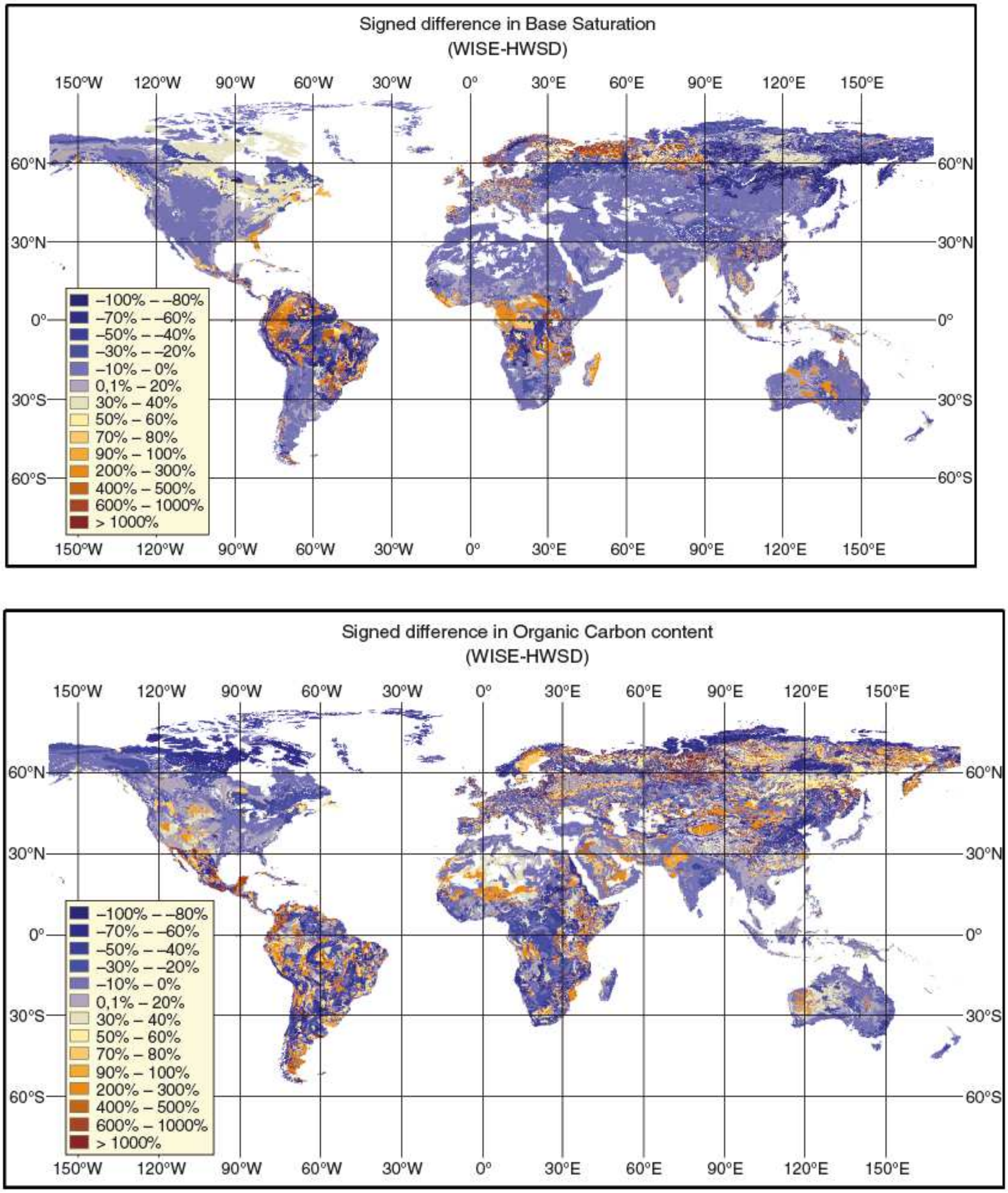

Figure 5 Signed differences in the % divergence of base saturation (top) and organic carbon content (bottom) between the HWSD and WISE datasets. Blue areas represent regions where HWSD show lower values than WISE; red areas show regions where HWSD values are larger than WISE ones. (For generalizations concerning the mapped soil unit composition and soil depth, see text).

resampling for continuous data in an ESRI ArcGIS environment. Through image subtraction, we quantified the differences between the datasets. Inherent uncertainties as a result of aggregation steps and the lack of consideration of natural variability need to be considered when analyzing the results (Batjes, 2006).

Determination of crop-suitable areas. We based our crop suitability analysis on fuzzy logic principles (Figure 2) (Burrough et al., 1992). Growth likelihood curves (from 0 to 1) for each crop were derived from Sys et al. (1993) (Figure 3). The growth likelihood of each crop and its corresponding growth limiting property were determined for each pixel. We compared the growth likelihoods for each crop (fuzzy OR rules) and then chose the lowest growth likelihood at a given pixel for each crop across all parameters (aggregation via fuzzy MIN).

The crop with the greatest growth likelihood was taken as the most suited for that location. This was determined by comparing the minimum growth likelihoods across all crops (fuzzy AND rules) and then selecting the crop with the highest growth likelihood (fuzzy MAX). If two or more crops had the same growth likelihood, a separate category was assigned (‘more than one’).

Four growth performance categories were applied as defined by Sys et al. (1993) and (FAO, 1976):

1. 0–0.4 Pixel not suitable for crop growth (N1 ⁄ N2) (none).
2. >0.4–0.6 Pixel marginally suitable for crop growth (S3).
3. >0.6–0.8 Pixel suitable for crop growth (S2).
4. >0.8–1 Pixel highly suitable for crop growth (S1).

Table 4 Overall differences between the two climate datasets for temperature (T) and precipitation (prec) considering mean global annual values only for the northern hemisphere (NH) or only for the southern hemisphere (SH). Difference = KCM values)WorldClim values. % Difference = [(KCM values) WorldClim values) ⁄ WorldClim value]*100

	WorldClim	KCM	Difference	
	°C	°C	°C	% Difference
T global	8.2	8.1	−0.1	−1.2
T NH	5.1	4.9	−0.2	−3.9
T SH	21	21.1	0.1	0.5
	mm	*mm*	*mm*	
Prec global	701	852	151	22
Prec NH	599	773	174	29
Prec SH	1119	1176	57	5

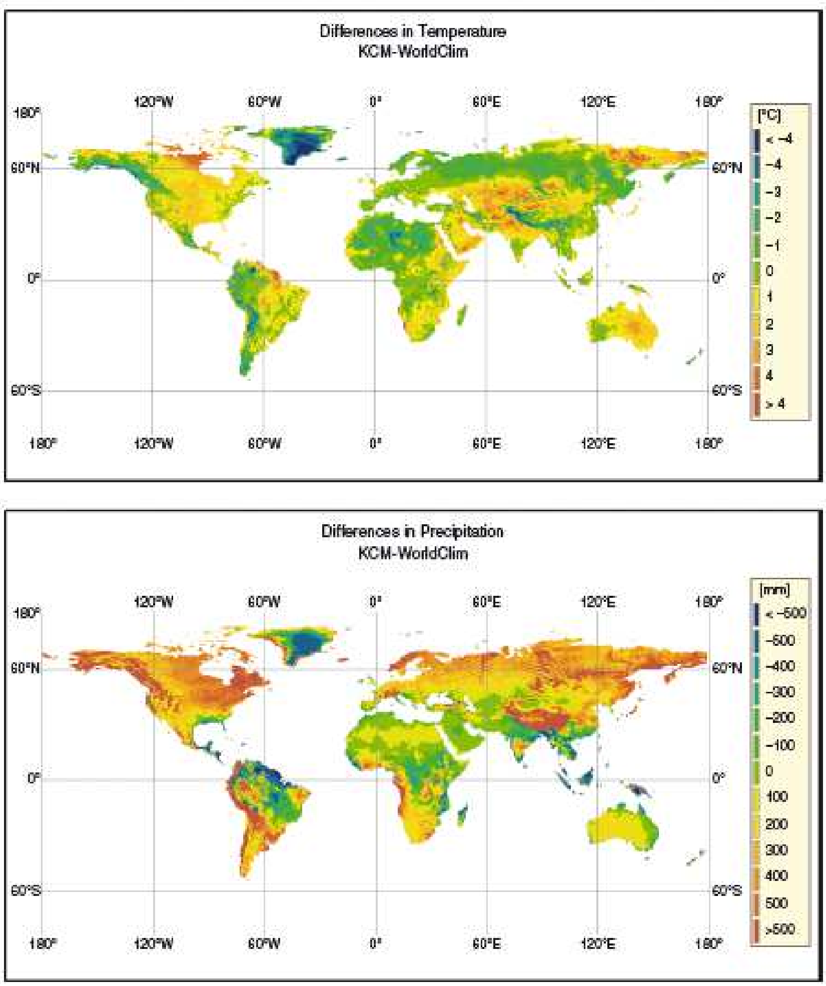

Figure 6 Signed difference between KCM and WorldClim temperatures in LC (top) and signed difference between KCM and WorldClim precipitation in mm (bottom). Red positive values show an overestimation of the KCM values in relation to the WorldClim ones; blue negative values represent an underestimation.

Table 5 Crop-suitable areas for each crop according to the soil database used [Harmonized World Soil Database (HWSD) in the upper part of the table

		1 km HWSD_WC_1				10 km HWSD_WC_10				67 km HWSD_WC_67				HWSD_KCM_67			
# in GIS	Crop	S	%	SC	%	S	%	SC	%	S	%	SC	%	S	%	SC	%
1	Barley	32680816	16.1	18880340	9.3	323065	16.0	195723	9.7	7190	16.2	4268	9.6	7190	16.2	4200	9.5
2	Cassava	6980851	3.4	6546034	3.2	75675	3.8	64058	3.2	1566	3.5	1429	3.2	1566	3.5	1573	3.6
3	Groundnut	6438674	3.2	8730212	4.3	64101	3.2	64387	3.2	1393	3.1	1400	3.2	1393	3.1	1481	3.3
4	Maize	7486402	3.7	1198633	0.6	74844	3.7	13210	0.7	1602	3.6	297	0.7	1602	3.6	285	0.6
5	Millet	4833958	2.4	4375358	2.2	47971	2.4	44719	2.2	1070	2.4	1007	2.3	1070	2.4	948	2.1
6	Oil palm	40242543	19.8	10254034	5	399157	19.8	101152	5.0	8808	19.9	2222	5.0	8808	19.9	1777	4.0
7	Potato	735230	0.4	249705	0.1	7390	0.4	2497	0.1	166	0.4	48	0.1	166	0.4	65	0.1
8	Rapeseed	0	0	156838	0.1	5	0.0	1609	0.1	0	0.0	34	0.6	0	0.0	35	0.1
9	Rice	1756141	0.9	1182448	0.6	17331	0.9	11717	0.6	393	0.9	276	0.6	393	0.9	269	0.6
10	Rye	0	0	0	0	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0
11	Sorghum	1468687	0.7	3699102	1.8	15872	0.8	43330	2.2	383	0.9	966	2.2	383	0.9	975	2.2
12	Soy	5594711	2.8	541560	0.3	53895	2.7	5733	0.3	1186	2.7	117	0.3	1186	2.7	121	0.3
13	Sugarcane	9758356	4.8	2645419	1.3	93511	4.6	25689	1.3	2089	4.7	577	1.3	2089	4.7	616	1.4
14	Sunflower	39151	0.02	886932	0.4	403	0.02	8843	0.4	8	0.0	166	0.4	8	0.0	130	0.3
15	Wheat	2755647	1.4	13942298	6.9	26726	1.3	142557	7.1	591	1.3	3194	7.2	591	1.3	3174	7.2
126	None	25953176	12.8	114712935	56.4	253084	12.6	1137368	56.5	5513	12.5	24931	56.3	5513	12.5	25578	57.8
127	More than one	56671127	27.9	15393622	7.6	562328	27.9	151960	7.5	12339	27.9	3333	7.5	12339	27.9	3070	6.9
	Total suitable	177442294	87.2	88682535	43.6	1762274	87.4	877184	43.5	38784	87.6	19334	43.7	38784	87.6	18719	42.3
1	Barley					39084	1.9	66687	3.3	856	1.8	1426	3.1	856	1.8	962	2.1
2	Cassava					203093	9.8	127371	6.2	4025	8.5	2547	5.6	4025	8.5	2829	6.2
3	Groundnut					0	0.0	14166	0.7	0	0.0	369	0.8	0	0.0	316	0.7
4	Maize					0	0.0	2747	0.1	76	0.2	133	0.3	76	0.2	265	0.6
5	Millet					1261	0.1	29492	1.4	68	0.1	581	1.3	68	0.1	520	1.1
6	Oil palm					401704	19.5	87509	4.3	9171	19.4	1993	4.4	9171	19.4	1434	3.2
7	Potato					0	0.0	2446	0.1	157	0.3	46	0.1	157	0.3	56	0.1
8	Rapeseed					0	0.0	19849	1.0	120	0.3	560	1.2	120	0.3	346	0.8
9	Rice					9283	0.4	16557	0.8	225	0.5	318	0.7	225	0.5	355	0.8
10	Rye					0	0.0	1462	0.1	17	0.0	43	0.1	17	0.0	16	0.0
11	Sorghum					13095	0.6	89652	4.4	497	1.1	1878	4.1	497	1.1	1578	3.5
12	Soy					1950	0.1	61872	3.0	425	0.9	1363	3.0	425	0.9	1444	3.2
13	Sugarcane					1	0.0	12219	0.6	172	0.4	326	0.7	172	0.4	376	0.8
14	Sunflower					89469	4.3	88280	4.3	1989	4.2	1799	4.0	1989	4.2	1431	3.1
15	Wheat					144229	7.0	116304	5.7	2950	6.2	2641	5.8	2950	6.2	2268	5.0
126	None					49081	2.4	1081644	52.8	3591	7.6	24648	54.2	3591	7.6	29351	64.5
127	More than one					1111778	53.9	231578	11.3	22936	48.5	4845	10.6	22936	48.5	3728	8.2
	Total suitable					2014947	97.6	968191	47.2	43684	92.4	20868	45.8	43684	92.4	17924	37.9

HWSD, Harmonized World Soil Database. WISE in the lower part of the table; the applied resolution of the input variables (km estimates roughly at the equator) and corresponding climate input used (WC for WorldClim; KCM for Kiel Climate Model). S stands for runs that include only topsoil and topographic constraints; SC stands for runs that include topsoil topographic and climate constraints. % equals the share of each crop in the total available land surface (suitable and non-suitable).

We performed two sets of model runs: (i) with only terrain and topsoil constraints for either soil database at three resolutions (coarse, medium, high) (s in the tables), and (ii) with terrain, topsoil and climate constraints (sc in the tables). The latter resulted in the combination of data as shown in Table 2.

Comparison of crop-suitable areas with actual harvested areas. We compared the results from the medium resolution runs for all constrains with the harvested areas of maize, rice and wheat as determined by Ramankutty et al. (2008) for the year 2000. This allowed us to make inferences about which soil datasets reflected most closely the historical distribution of crops. An exact matching was not expected as inherent uncertainties from the input datasets, and the simplification of crop growth requirements cannot be incorporated into our biophysical model. We used the comparative reclassification methodology as described in Figure 4.

Table 6 Absolute differences in crop-suitable areas (%) between the soil databases for the medium (5 arc min) resolution using WorldClim climate variables on a global scale as well as for the three selected countries where underlying soil input databases are of increasing similarity (China Brazil USA). S stands for runs that include only topsoil and topographic constraints; SC stands for runs that include topsoil topographic and climate constraints. Calculation example: world_s_barley = abs (WISE_WC_10_s%) HWSD_WC_s_10%) = abs (1.9) 16) = 14.1

		World		China		Brazil		USA	
# in GIS	Crop	S	SC	S	SC	S	SC	S	SC
1	Barley	14.1	6.5	17.3	9.7	1.0	1.0	18.0	10.2
2	Cassava	6.1	3.0	4.4	2.0	10.0	11.5	14.8	5.1
3	Groundnut	3.2	2.5	7.8	0.0	0.5	0.1	0.0	0.5
4	Maize	3.7	0.5	2.3	1.1	0.5	0.1	7.0	0.8
5	Millet	2.3	0.8	0.1	0.1	0.1	0.2	0.2	1.4
6	Oil palm	0.3	0.8	16.9	0.6	28.2	17.9	13.3	0.0
7	Potato	0.4	0.0	0.2	0.2	0.0	0.0	0.0	0.9
8	Rapeseed	0.0	0.9	0.0	0.9	0.0	0.0	0.0	3.0
9	Rice	0.4	0.2	0.3	1.8	3.8	3.4	1.6	4.7
10	Rye	0.0	0.1	0.0	0.0	0.0	0.2	0.0	0.0
11	Sorghum	0.2	2.2	1.2	0.4	0.2	5.1	0.1	3.8
12	Soy	2.6	2.7	1.9	0.0	0.2	3.6	2.8	0.9
13	Sugarcane	4.6	0.7	5.3	1.4	0.0	0.1	1.6	2.9
14	Sunflower	4.3	3.9	4.1	0.4	0.2	0.1	3.6	2.6
15	Wheat	5.7	1.4	1.0	2.8	0.8	0.1	6.0	10.2
126	None	10.2	3.7	0.5	0.2	42.4	42.7	3.8	2.5
127	More than one	26.0	3.8	43.7	9.9	10.3	8.6	20.7	4.4

HWSD, Harmonized World Soil Database.

Results

Comparison of soil and climate datasets

Soil dataset. Harmonized World Soil Database showed lower parameter estimates (between 2 and 25%) than WISE in all parameters. Exceptions were organic carbon (0.3%) and salinity and sodicity (43% lower) (Table 3). Country-specific deviations were lowest in the USA (between 0 and 29%), followed by China (2–44%) and Brazil (4–90%) (Table 3, Figure 5).

Climate dataset. The KCM underestimates global annual temperatures (0.1 °C or 1.2%) compared with the WorldClim values especially in the northern hemisphere (Table 4). The KCM underestimates temperatures in mountainous regions, in Siberia, Greenland and the Sahara. Over-estimations occur in continental areas (Figure 6). The KCM overestimates precipitation globally (22%) and more markedly in the northern hemisphere (Table 4). Underestimations occur in Greenland, the Gulf Coast, the Caribbean, northern South America and South East Asia. Over-estimations are in mountainous areas and on the eastern side of continents (Figure 6).

Crop-suitable areas

The effect of the soil database on crop suitability. These results are the outcome of simulations based on soil and terrain components only. Areas of potential crop growth occur on ca. 87% of the earth's land surface in HWSD-based runs and up to 98% in the WISE-based computations (Tables 5 and 6). The HWSD-based runs were more suitable for barley on 14% of the total land surface (Table 6, Figure 7). Differences between the suitable areas for each crop were greatest in China and least in Brazil and the USA (Table 6, Figure 8). The greatest differences between the runs can be seen in the areas unsuitable for crop growth. By determining the limiting parameter for the areas unsuitable for crop growth, we see that high base saturation values from the HWSD in the Amazon basin are responsible for this (Figure 12). In the Kalahari, low organic carbon makes it unsuitable.

The effect of climatic input on crop suitability. The addition of climatic constraints reduces the amount of suitable areas to less than half of the earth's land surface with differences between climate models being greatest in WISE-based runs (Table 5, Figure 9). Areas in northern latitudes and with low precipitation are unsuitable for crop growth. In some areas, slight differences were observed for the south and west of South America where less growth was found in KCM-based runs. Regional discrepancies in soil databases because of differences in the underlying soil mapping units are reduced as some

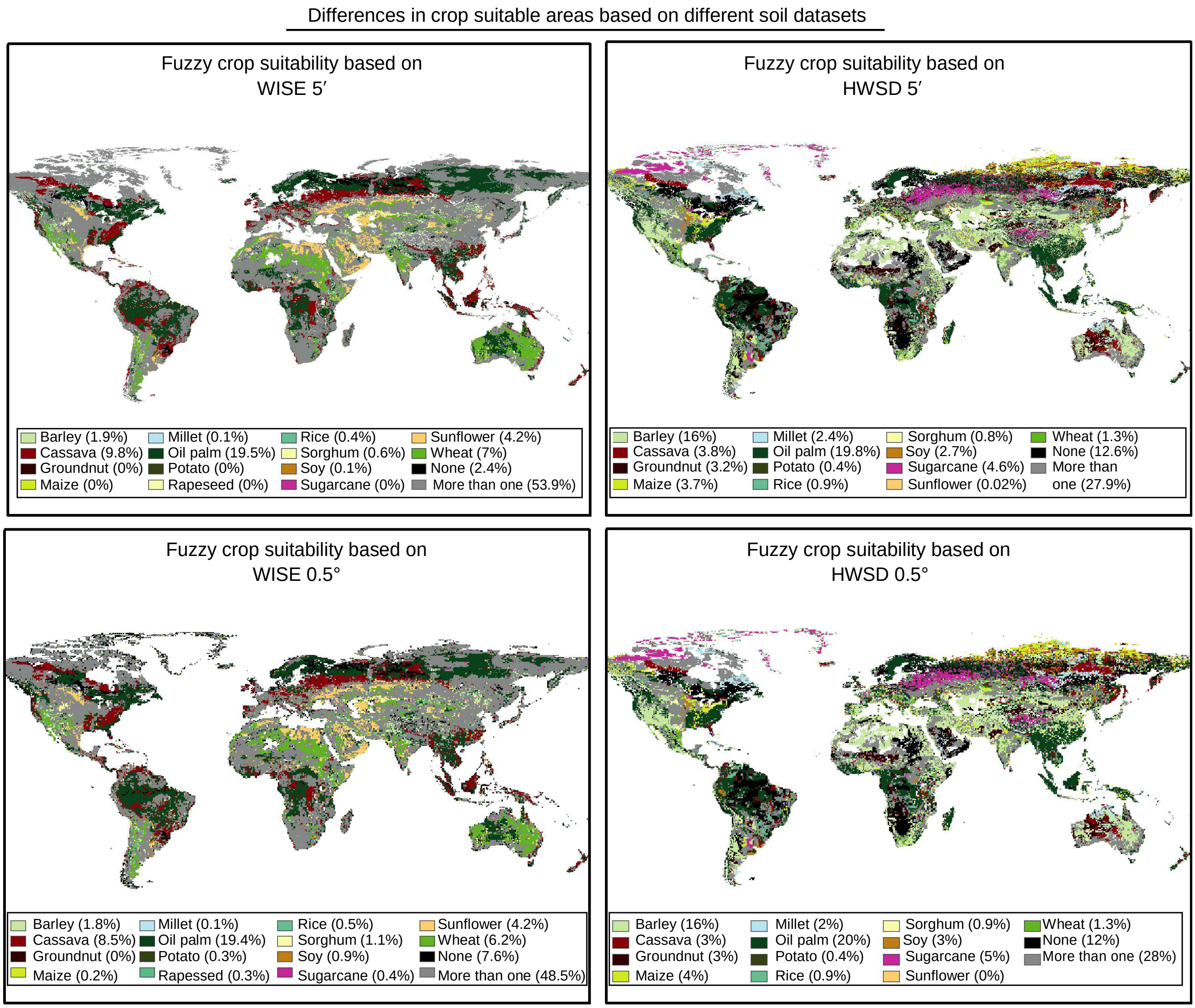

Figure 7 Geographic differences in the distribution of crops based on the ISRIC-WISE soil database (left) or the Harmonized World Soil Database soil database (right) at the middle (5 arc min or 10 km) (top) and low (0.5 arc degrees or 67 km) (bottom) resolutions.

crop types become no longer viable, such as with oil palm in the USA or sugarcane in Siberia (Table 5, Figures 8 and 9).

The effect of grid size resolution on crop suitability. The resolution of the input used variables had little to no effect on the overall extent of crop-suitable areas or the global share of each crop (Table 5). Nonetheless, at the highest grid size resolution (30 arc s), choosing the optimal location for each crop is more accurate. Distinctive landscape features such as hills and valleys, riverbeds and plateaus can be discerned – impossible at lower resolutions (Figure 10). The most distinct placement also coincides with areas of small mapping units, such as in China or Europe (Figure 8).

Comparison of crop-suitable areas with actual harvested areas

Potentially suitable areas using either soil dataset in combination with WorldClim coincided with >70% of the harvested land for 2000 for wheat, maize or rice as determined by SAGE (Center for Sustainability and the Global Environment at the University of Madison, Wisconsin) (Ramankutty et al., 2008) (Table 7). Global differences between soil datasets were greatest for wheat

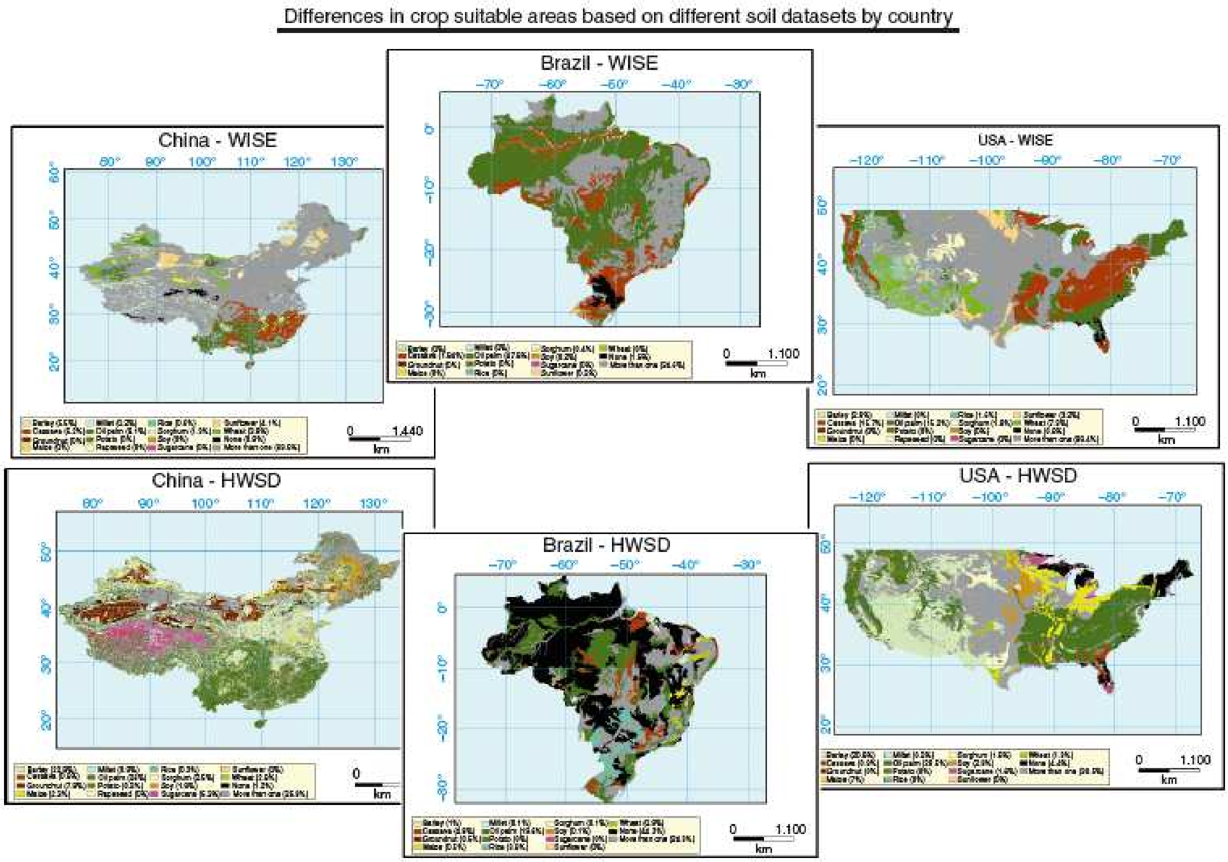

Figure 8 Differences in crop-suitable areas according to the applied soil database (Top: WISE; Bottom: Harmonized World Soil Database) for China, Brazil and the USA (from left to right) in the medium resolution of 5 arc min. The soil mapping units vary from similar for either soil database in the case of the USA to highly different in the case of Brazil and China. Therefore, the resulting crop distribution patterns are similar for the USA but highly different for China. As soil mapping units vary, the input parameter values are also different for the countries; therefore, crop suitability is also different.

suitable areas (Figure 11). Regional differences are evident for the wheat growing areas of the mid US where WISE underestimates large areas whereas HWSD overestimates them (Figure 11).

Discussion

Dataset comparisons

Comparison of the datasets for either soil or climate revealed that global differences in the analysed parameters can exhibit large discrepancies but can also be small. Differences between the hemispheres can be seen for both temperature and precipitation. The larger landmasses of the northern hemisphere pose particular problems for modelling (Roeckner et al., 2004). Differences in soil property estimates are largest in areas where the underlying input soil databases differed most, such as in China. Here, the mapping units of the HWSD were artificially disaggregated into individual pixels, thus disrupting natural soil patterns (FAO, IIASA, ISRIC, ISS-CAS & JRC, 2009). Areas based on SOTER show discrepancies in the geographic extent of soil mapping units. Soil property estimates in areas with the same underlying soil mapping units (DSMW areas) show the least differences. Marginal differences still occur as each dataset is based on different global soil profiles and on different clustering procedures (Batjes, 2002b). Soil parameters measured on a regular basis, such as pH and organic carbon, exhibit less differences between datasets than variables such as sodicity and salinity that are measured less frequently or are calculated from other parameters (Batjes, 2002b).

In our comparison of soil datasets, we disregarded that some mapping units may have up to eight further component soils apart from the dominant one and that the dominant soil may occupy <50% of the mapping unit. However, dominant soils comprise >50% of the mapping unit in >75% of all

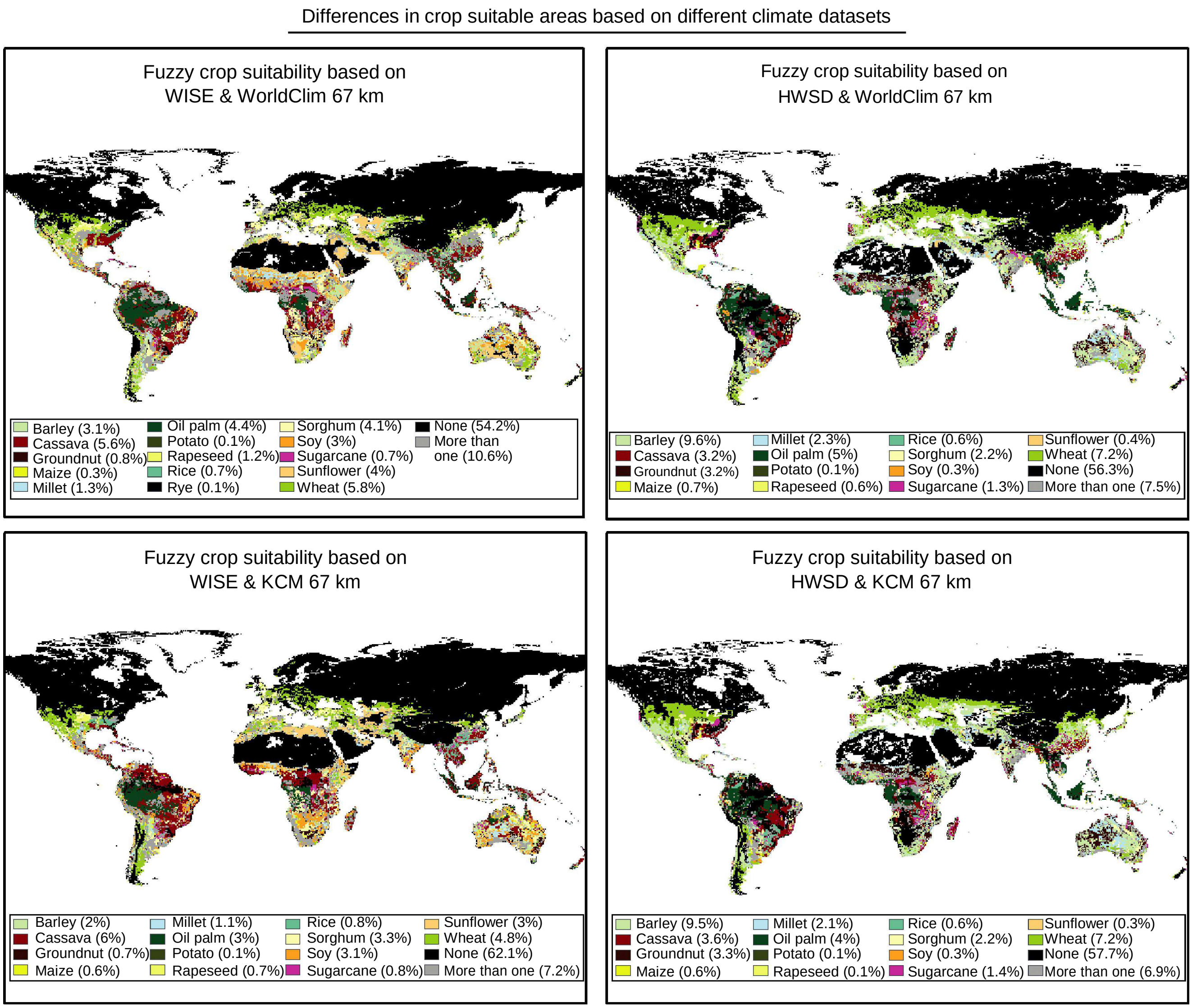

Figure 9 Geographic differences in the distribution of crops based on the WISE soil database (left) or the Harmonized World Soil Database soil database (right) using the WorldClim data (top) or Kiel Climate Model (bottom) input variables.

mapping units of the ISRIC-WISE dataset and in 66% of the mapping units of the HWSD. Our crop suitability analysis may give altered results when all component soils and their actual share value within each soil mapping unit are considered for the computation of parameter value estimates for each pixel.

Effect on crop suitability

Soil datasets. Soil and terrain constraints alone do not strongly limit crop growth as >80% of the global land surfaces are suitable for crops using either database. The estimates of soil properties influence the location of crop-suitable areas, the types of crops and the ability to distinguish between crop types. In particular, high values of pH, base saturation and organic carbon limit crop growth. Hence, differences in these parameters between the soil databases can be used to define areas as suitable or unsuitable for crops. For enhanced model performance, the soil databases need to provide higher quality and spatially more detailed but geographically uniform parameter value estimates. The WISE dataset consists of geographically uniform, but coarse quality data. The HWSD dataset provides geographically unequally distributed data quality with some areas being spatially more explicit than WISE.

Climate datasets. The limited difference between the climate datasets does not have a drastic effect on crop

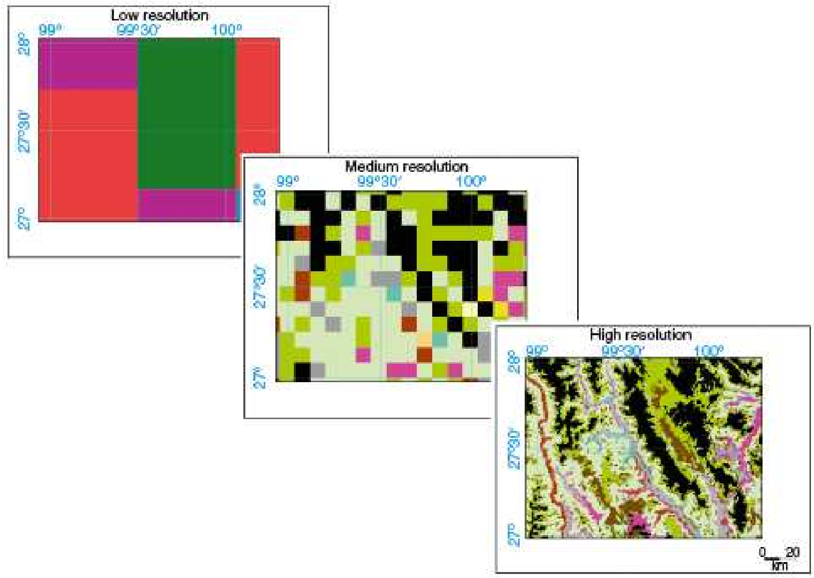

Figure 10 Differences in qualitative placement of crops with increasing spatial resolution for an exemplary region in China. At the low resolution, no distinctions can be made of landscape features but this becomes possible for the high resolution areas.

Table 7 Matching of the crop suitability results for the runs on a 10-km resolution using WorldClim data with harvested areas of maize rice and wheat of the year 2000 as determined by (Ramankutty et al. 2008) using either the Harmonized World Soil Database (HWSD) or the WISE soil database. Negative values denote underestimations by our model, positive values overestimations; the larger the number the greater the deviations from the harvested areas. 0 (in bold) shows the amount of overlap.

		HWSD		WISE	
		Count	%	Count	%
Maize	−3	23	0.0	10	0.0
	−2	535	0.0	474	0.0
	−1	431908	21.8	440385	21.9
	0	**1405723**	**71.0**	**1425567**	**70.8**
	1	76073	3.8	89864	4.5
	2	51832	2.6	48770	2.4
	3	14870	0.8	9809	0.5
Rice	−3	1874	0.1	1842	0.1
	−2	3897	0.2	2882	0.1
	−1	260600	13.2	192180	9.5
	0	**1642859**	**82.9**	**1664967**	**82.6**
	1	55414	2.8	119294	5.9
	2	15165	0.8	30383	1.5
	3	1155	0.1	3331	0.2
	−3	167	0.0	193	0.0
Wheat	−2	1653	0.1	2143	0.1
	−1	270843	13.7	347184	17.2
	0	**1429538**	**72.2**	**1393707**	**69.2**
	1	217115	11.0	153261	7.6
	2	58336	2.9	109810	5.4
	3	3312	0.2	8581	0.4

suitability as the climate datasets diverge most strongly in areas where plant growth is not possible. Inaccuracies in the results from the KCM need to be considered for future climate scenarios where temperatures may rise in northern latitudes and rainfall patterns may change in mid latitudes.

Constraints because of low temperatures account for ca. 40% of the global land surface outweighing all other limitations. The Global Agro-ecological zones project (Fischer et al., 2002) uses a different methodology for assessing climate constraints (Length of Growing Period) and determined 26% of the land surface to be limited by temperature.

All constraints. The inclusion of all constraints in the model subdivides the geographic extent of soil mapping units on a pixel-by-pixel basis. In mountainous or in climatic areas with narrow transition zones, crops will vary from pixel to pixel instead of occupying large continuous areas such as in lowlands. With increased grid size for input data, landscapes become more fragmented and the identification of areas suited to crops becomes more accurate.

In the discussion on input parameter uncertainties, the definition of crop growth requirements cannot be left out. The definitions we used are based on data from more than 15 yr ago and do not take into account advances made in crop varieties, genetic modifications and climatic adaptation of commercial crops. The selection of crops based on prices, accessibility to markets and other socio-economic factors are ignored. Management strategies that improve certain conditions such as water availability and other soil qualities

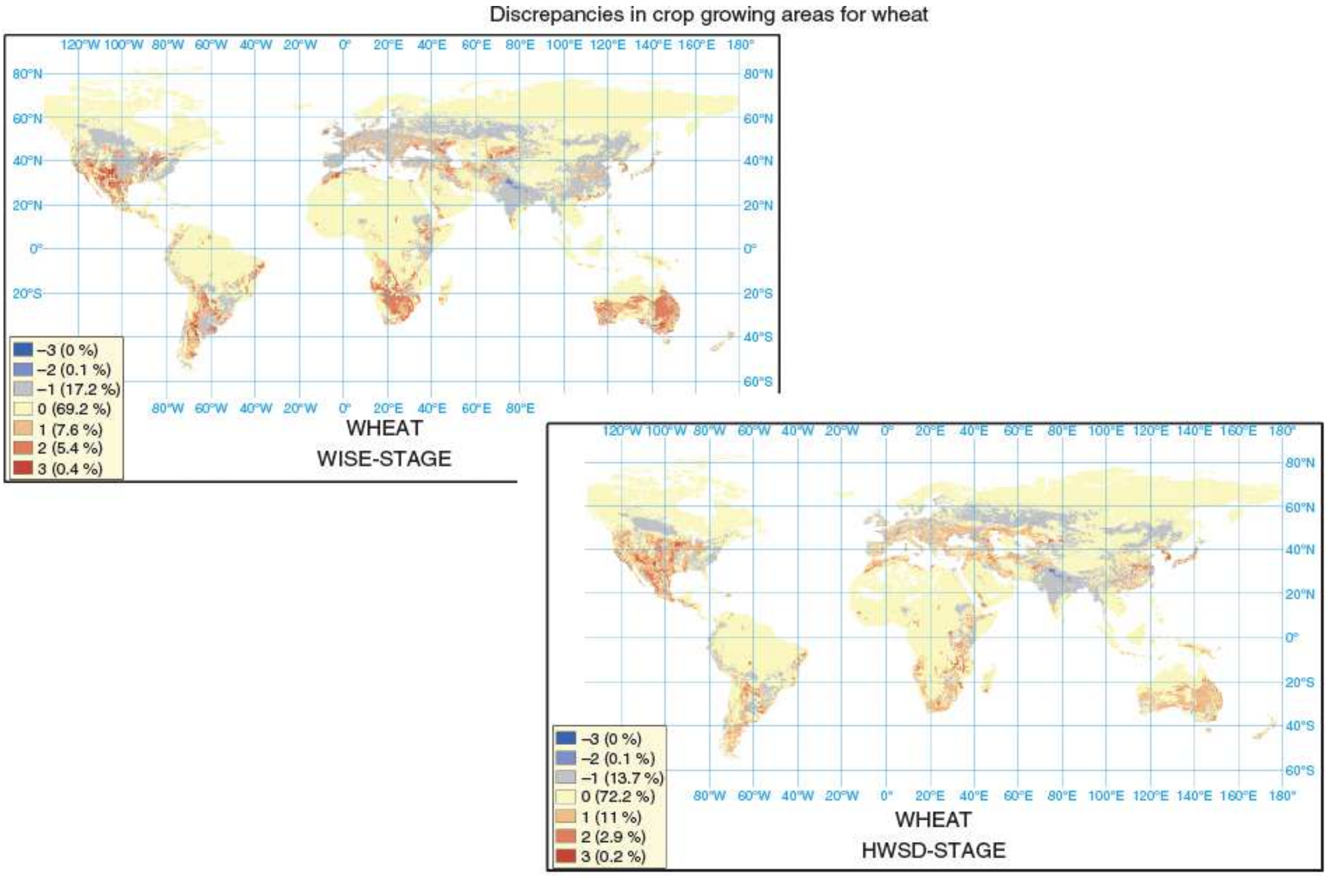

Figure 11 Differences in crop growing areas between the harvested areas as determined by Ramankutty et al. (2008) for wheat versus the crop-suitable area determined by the WISE soil database and the WorldClim dataset on a 5-arc min resolution (left) or the Harmonized World Soil Database dataset (right). Blue colours show underestimations of cropping extent and intensity by the crop suitability analyses; red areas and overestimation. Deviations are indicated by the intensity of the colour and the associated value.

are not considered. Such practices may allow other areas currently not suitable to become suitable for crops.

Despite the constraints and uncertainties in the methodology, the potential global distribution of crops can be predicted with an accuracy of >70%. Some areas currently covered by forest (e.g. parts of the Amazon basin and Northern Boreal forests) are not suitable for crop growth as also shown by Fischer et al. (2002). The Amazon region has extensive areas with soils of inadequate quality, so that conversion to agricultural land on an extensive basis is unlikely. Northern boreal forests are constrained by their climate although this may not be so true in the future (Ramankutty, Foley et al. 2002).

Conclusion

We conclude that the quality of climate data is similar between station data and model outputs whereas that of global soil databases is very different and offers marked regional discrepancies. Hence, the extent of crop-suitable areas and the choice of the optimal crop differ most when using either soil databases but are similar whilst applying either climate dataset. Increased grid size resolution enhances the fragmentation of the landscape to give a more accurate location of crops.

For optimal outputs from agro-ecological models, the input databases have to deliver uniform and high quality data on a detailed spatial scale. Simply using smaller pixels does not result in the latter. Rather, global soil models should offer smaller scale geographic extents of the soil mapping units. It is hoped that initiatives such as the Global Soil Map project (IUSS, 2009) or an updated HWSD with the aid of further SOTER databases will provide a better basis for enhanced crop suitability modelling.

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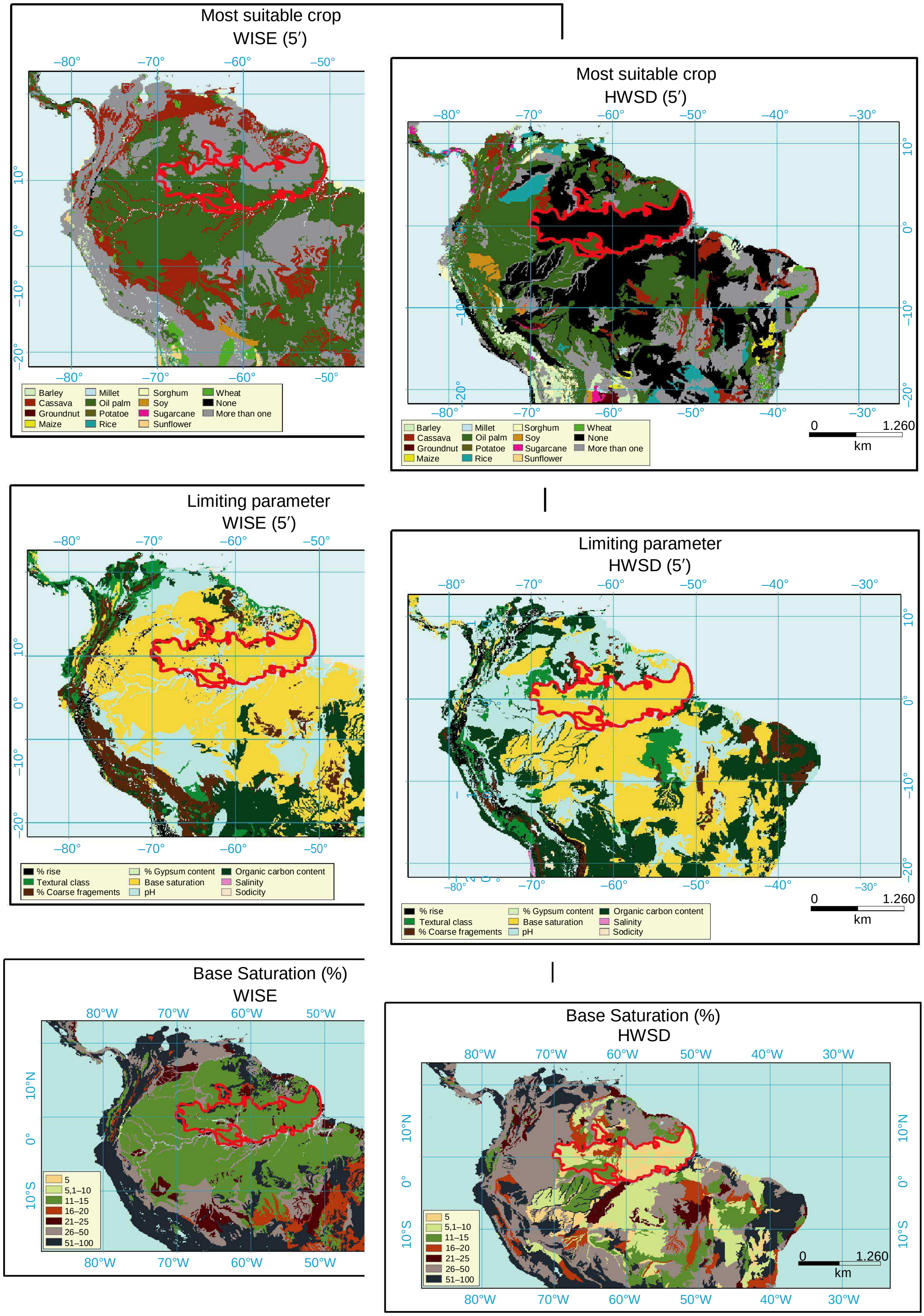

Figure 12 Examples which contrast the effect of the differences in the limiting parameter values between WISE and HWSD, Harmonized World Soil Database (HWSD)-based runs on a 5- arc min resolution for the Amazon forest. The lower values of base saturation in the HWSD result in growth limited areas (red delineated area), whereas the larger WISE values allow for the growth of oil palm and ‘more than one’ crops.

and Ariane Hartmann for their work on the comparison of the two soil and climate datasets.

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A Comparison of Using Dominant Soil and Weighted Average of the Component Soils in Determining Global Crop Growth Suitability

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Abstract

Soil parameters represent key data input for crop suitability analysis. Soil databases are complex offering soil mapping units made up of various component soils. In the case of the Harmonized World Soil Database there can be up to 8 component soils per unit. In roughly 1/3 of soil mapping units, the additional component soils take up more than 50% of the pixel share value. The soil parameter value estimate, such as pH, salinity and organic carbon content, may differ between the value of the dominant soil component and the weighted average of the values of all component soil. Understanding the effect of these differences on crop model outputs may allow quantifying the error. In this study, we show the changes in crop suitability of 15 crops while using the parameter value estimates of the dominant soils versus a weighted average of the component soils. In the case of the latter, global crop suitability amounts to 54.5% of the earth's land surface–1% more than when using the values of just dominant soils. Intrinsic regional differences in the quality of the soil database influence the distribution of crop suitability classes especially in areas where share values of the dominant soil are low. The uncertainty range for the use of dominant versus component soils on the overall global crop suitability could be considered to be 1%, while that of each suitability class can amount to up to 4%.

Keywords: crop suitability, HWSD, quality control, dominant soil, mapping units, component soils

1. Introduction

Ensuring food security for the global population is already challenging in current times and will be even more, when population rises up to around 8.3 billion by 2030 (UNDP, 2008). Enhanced food production relies on three factors: increased yield, enhanced cropping intensity and the expansion of agricultural land (FAO, 2003). In 2009, the total amount of agricultural and permanent crops amounted to 2.5 billion ha which equals about 19% of the earth's land surface (Bontemps, Defourny, Van Bogaert, Arino, & Kalogirou, 2009). In the last four decades of the past century, 172 million ha of land have been added in developing countries (FAO, 2003). To ensure global food security, an additional 120 million ha of converted land are projected to be necessary until 2030 and an extra 5% will be necessary up to 2050 (Bruinsma, 2009). Most land is expected to be transformed in South America and Sub Saharan Africa (Fischer, 2000).

Models based on climate and soil inputs can help discern the areas where crops can grow optimally for given natural conditions. Fischer et al. (2002) showed that roughly 2.8 billion ha are to some degree suitable for rain-fed agriculture and Avellan, Zabel, and Mauser (2012) showed that about a quarter of the earth's land surface is suitable to highly suitable for the rain-fed growth of 15 major crops (Avellan, Zabel, & Mauser, 2012; Fischer, 2002) . Both authors base their different models (Global agro- ecological zones versus fuzzy logic crop suitability) on global soil and climate databases. However, global soil databases are scarce and rely on patchy soil sampling. Few sets exist, such as the Harmonized World Soil Database (HWSD) (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009) and the ISRIC-WISE derived soil properties on a 5 by 5 arc minute grid (Batjes, 2006). Global Climate Datasets are more varied. Past climate data can be obtained from interpolated station data (WorldClim), reanalysed forecasts (ERA) or hind-casted climate models (ECHAM, HadCM).

Avellan et al. (2012) showed that the quality of climate inputs is quite homogenous while global soil databases can differ widely. The choice of the database can have a strong effect on the amount and distribution of crop suitable areas, leading to a 10% difference between the two most common global soil datasets (Avellan et al., 2012). Soil databases are immensely complex and the quality of the data is geographically diverse. For example, the HWSD is made up of four different input databases–each covering different areas of the world, using different sampling and compilation methods (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009) (see Figure 1). Each pixel can contain up to 8 component soils which may, in sum, have a larger share within the pixel than the dominant soil class (see mock up example in Figure 2). When taking component soil classes into account, the soil parameter value estimate for each given pixel may be different than that of the dominant soil mapping unit (i.e. dominant soil value for pH is 8, but that of the weighted average of all component soils is 7.8).

In order to enhance modelling results a balance between the quantity and quality of the used input parameters has to be maintained. While more parameters might refine the modelling results, poor quality parameters might, in fact, be counterproductive. A careful analysis of both the quality of the data as well as their influence on final results might inform the choice of parameters. In Avellan et al. (2012), we started our crop suitability analysis using only the parameter value estimates of the dominant soil mapping unit of the topsoil (0-30 cm) on a pixel by pixel basis. In comparison, the Global Agro-ecological zones studies, used soil parameters from all component soils, top- and subsoils (0-30 cm and 30 cm and below), phases as well as management practices (IIASA/FAO, 2012). It is clear to the authors that other parameters relevant to soil databases such as subsoil parameters (30 cm and below), including drainage, granularity or acidity, as well as phases and management practices can have drastic effects on crop growth (Benjamin, Nielsen, & Vigil, 2003; Kirchhof et al., 2000; Van den Akker, Arvidsson, & Horn, 2003).

To our knowledge, the use of parameters in crop suitability models has not been substantiated by the analysis of the quality of the data. The inclusion of factors is defended by referring to standard works (i.e. FAO manuals (FAO, 1976, 2007) or similar) without questioning the validity of the usage. It is our intent to enhance model complexity in a step-by-step approach while showing the error margins incurred. Analogous to the well-known uncertainty ranges of climate models we wish to demonstrate a similar approach in the use of crop suitability estimations. Here, we assessed the influence of the area-weighted average of the additional component soils of the soil mapping units of the topsoil, on the amount and distribution of crop suitable areas.

2. Materials and Methods

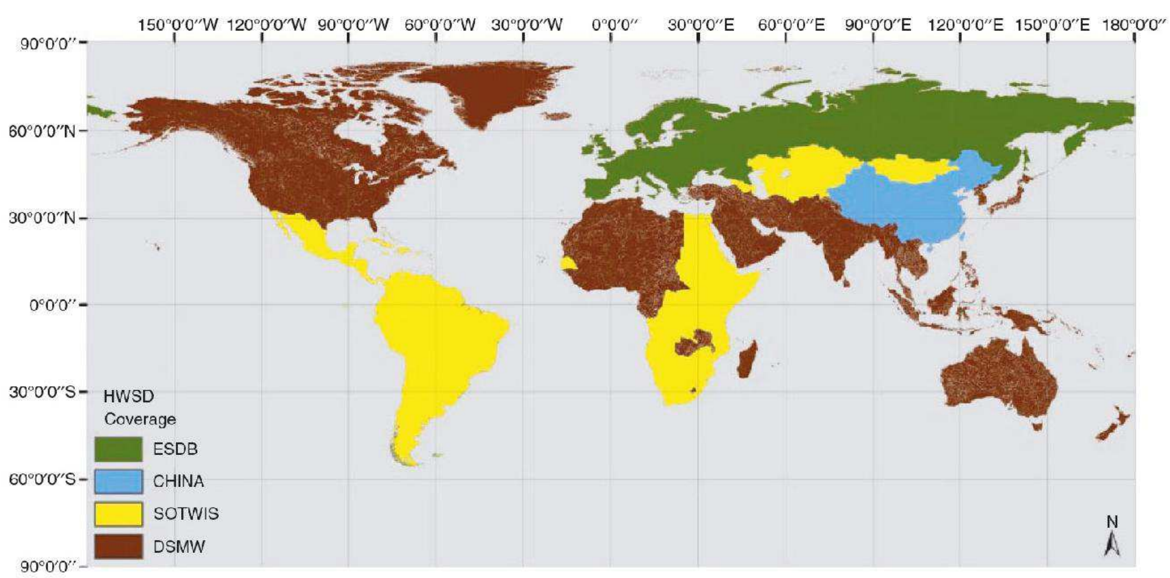


Figure 1. Distribution of the four underlying databases of the Harmonized World Soil Database (HWSD); European Soil Database (ESDB), Soil Map of China (CHINA), Soil and Terrain dataset (SOTWIS), Digital Soil Map of the World; adapted from (FAO, IIASA, ISRIC, ISS-CAS & JRC, 2009)

2.1 Datasets

We used the following datasets and parameters at 30 arc seconds resolution (1 x 1 km at the equator):

Harmonized World Soil Database (HWSD, version 1.1): dominant and component soil mapping units of the topsoil (0-30cm) as input for eight parameter value estimates–textural class (USGS), coarse fragments volume (%), gypsum (%CaSO4), base saturation (%), pH, organic carbon (%), salinity (dS/m) and sodicity (%).

WorldClim dataset (Hijmans, Cameron, Parra, Jones, & Jarvis, 2005): mean annual temperature and mean annual precipitation

SRTM30 global digital elevation model (Farr et al., 2007; USGS, 2000): slope computed as percent rise.

Regions were defined for their economic relevance in global trade as a biophysical crop model was coupled to a Global Equilibrium Model in a subsequent step (Table 1).

Table 1. Coding of the regions

Region code	Region name
AFR	Sub-saharan Africa
BEN	Belgium, Netherlands, Luxemburg
BRA	Brazil
CAN	Canada
CHI	China
FRA	France
FSU	Rest of former Soviet Republic
GBR	UK & Ireland
GER	Germany
IND	India
JPN	Japan
LAM	Rest of Latin America
MAI	Malaysia, Indonesia
MEA	Middle East, North Africa
MED	Spain, Portugal, Italy, Greece, Malta, Cyprus
MRC	Chile, Argentina, Uruguay, Paraguay
NAU	New Zealand, Australia
PAS1	Guayanas
PAS2	Iceland
PAS3	Switzerland
PAS4	Afghanistan, Pakistan
PAS5	Mongolia
REU	Austria, Estonia, Latvia, Lithuania, Poland, Hungary, Slovakia, Slovenia, Czech Republic, Romania, Bulgaria
RUS1	RUS1 (west)
RUS2	RUS2 (east)
SCA	Finland, Sweden, Denmark
SEA	Kambodscha, Laos, Thailand, Vietnam, Myanmar, Bangaldesh
USA	United States of America

2.2 Dominant vs. Component Soil Areas and Soil Parameter Value Estimates

Dominant soil is defined as the HWSD component soil with the largest share value irrespective of the fact that the other component soils together may have a larger share within one pixel. Soil parameter value estimates are the values each pixel has for a chosen parameter, i.e. pH, salinity, etc. In Figure 2 we have tried to show in a mock-up example how a pixel can be made up of several component soils and the effect the weighted average has on the parameter value estimate.

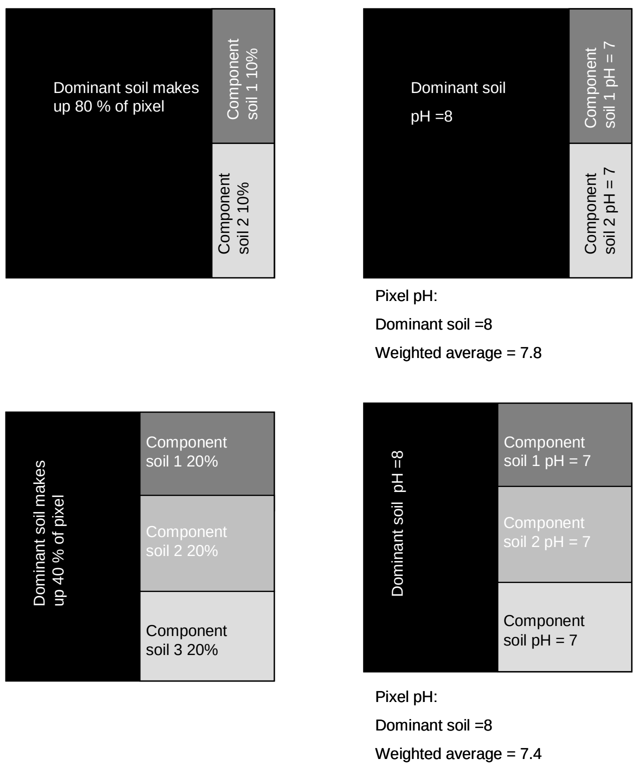


Figure 2. Mock -up examples of two pixels with different distributions of component soils (left); effect of using the weighted average on the overall parameter value estimate versus using that of the dominant soil (right)

We used GIS techniques to determine the area of prominence of dominant soils and compared it in size to that where component soils had higher percentages. We used Mondrian (version 1.2), an open source statistical analysis tool (University of Augsburg, 2012), to study the distribution of dominant soil units and component soil units. For the spatial representation of the soil units, a FORTRAN program was designed that allowed assigning the soil unit share to each pixel.

2.3 Determination of Crop Suitable Areas

We used the fuzzy logic approach as discussed in Avellan et al. (2012). Fuzzy classification methods define growth through membership functions and likelihoods (Burrough, MacMillan, & Deursen, 1992). The rationale behind this is that most soil parameters have a large error rate per se, due to sampling and handling errors, and crops are able to grow at various levels of these parameters (Rossiter, 1996). Thus strict Boolean classification systems may be too restrictive in growth ranges and areas. Fuzzy logic approaches have been used for a selected number of crops on limited study areas by other authors e.g. (Baja, Chapman, & Dragovich, 2002; Braimoh, Vlek, & Stein, 2004; Reshmidevi, Eldho, & Jana, 2009; Van Ranst, Tang, Groenemam, & Sinthurahat, 1996).

Raster-based soil, terrain and climate parameter values were matched on a sliding scale from 0 to 1 with their respective crop growth likelihoods as determined by (Sys, Van Ranst, Debaveye, & Beernaert, 1993) (Figure 3a). Subsequently, the most optimally matching crop was selected to be the most suitable for a given pixel. Each component soil was assigned one fuzzy value (Figure 3b). Depending on the number of component soils in each soil mapping unit, up to 8 fuzzy values per pixel were assigned. These were aggregated based on their weighted share value of the respective soil mapping unit. Component soils with high share values end up with a stronger influence on the final fuzzy value.

Crop growth abilities were then categorized into four subsets as defined by Sys et al. (1993) and (FAO, 1976). Fuzzy value between:

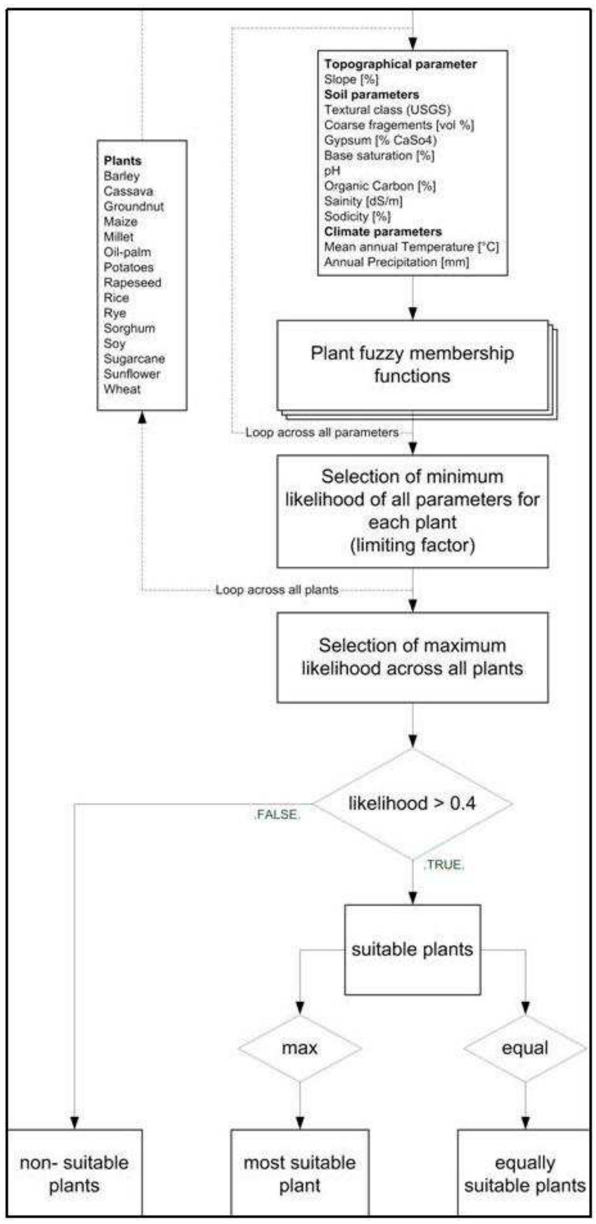
1) 0–0.4 Pixel not suitable for crop growth (N) (none).

2) 0.4–0.6 Pixel marginally suitable for crop growth (S3).

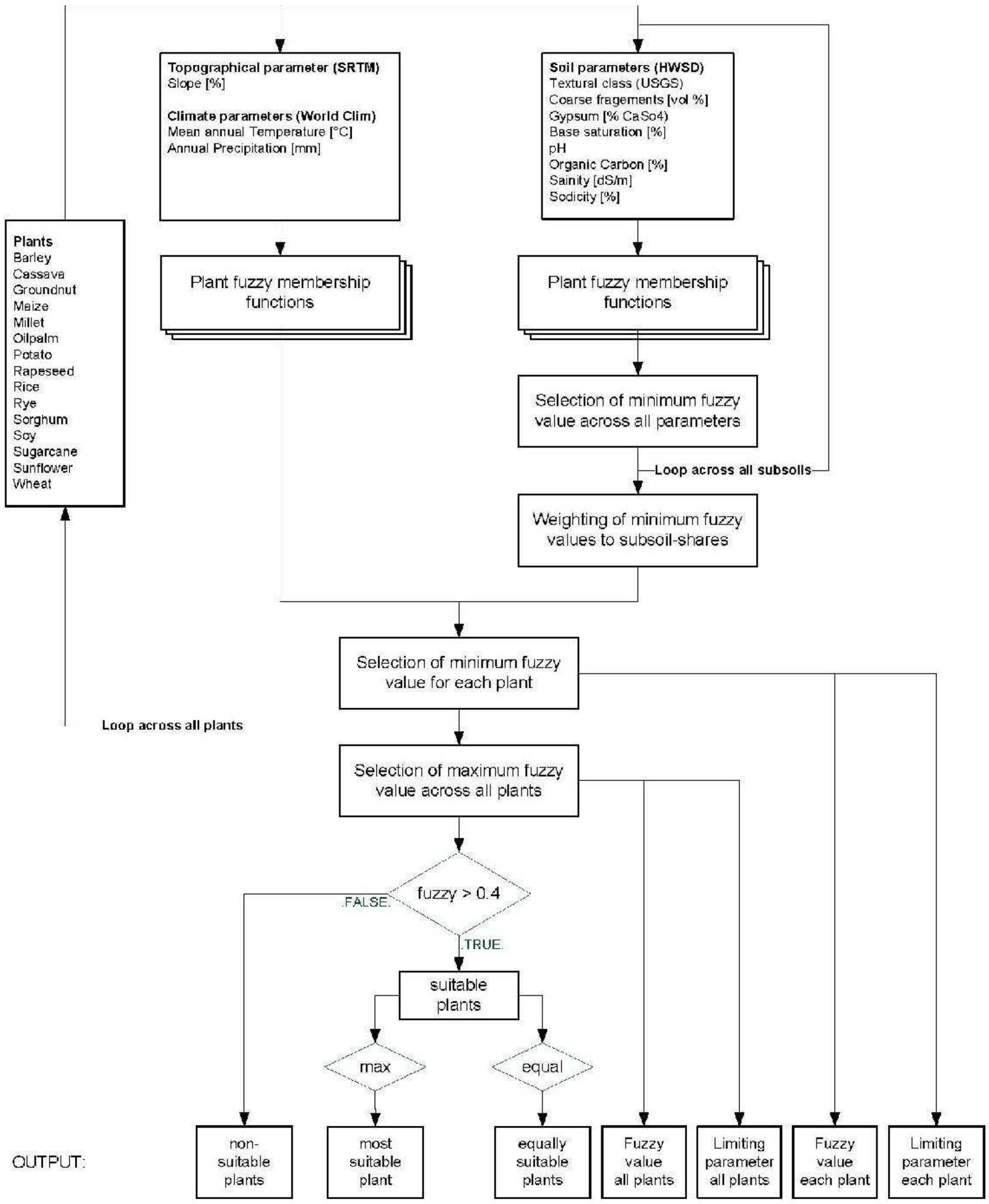
3) 0.6–0.8 Pixel suitable for crop growth (S2).

4) 0.8–1 Pixel highly suitable for crop growth (S1).

Pixels are subsequently transformed into land surfaces according to their location on the globe through a FORTRAN programme. The total land surface is considered except Antarctica.



(a)



(b)

Figure 3. Overview of the methodology of fuzzy logic crop suitability analysis using just the parameter value estimates of a) the dominant soil (top) or b) of all component soils (bottom)

3. Results

3.1 Dominant vs. Component Soil Areas

In 64% of all pixel the dominant soil holds more than 50% of the pixel's share value. When looking at specific major soil groups, some only exist as dominant soil types (i.e. Is-Lithosols, Ns-Nitosols, U-Rankers and W-Planosols). Most soils comprise only two component soils in their soil mapping unit (i.e. dominant soil plus one additional component soil). Few cases exist where soil mapping units have 6 or more component soils. The share value of the dominant soil component is very high in most of northern Asia, Greenland, the North America and large parts of Africa. These are areas where the dominant soil defines the parameter value estimate (grey areas in Figure 4). In the case of China, due to the way the database was produced, only one-the dominant-soil exists. In the Middle East, Central Asia, the Pacific and Australia, share values of the dominant soil component were very low. These are areas where the other component soils play a larger role in determining the parameter value estimates of the given pixel (black areas in Figure 4, see also mock up example in Figure 2). South America exhibits mostly areas with intermediate share values (data not shown explicitly).

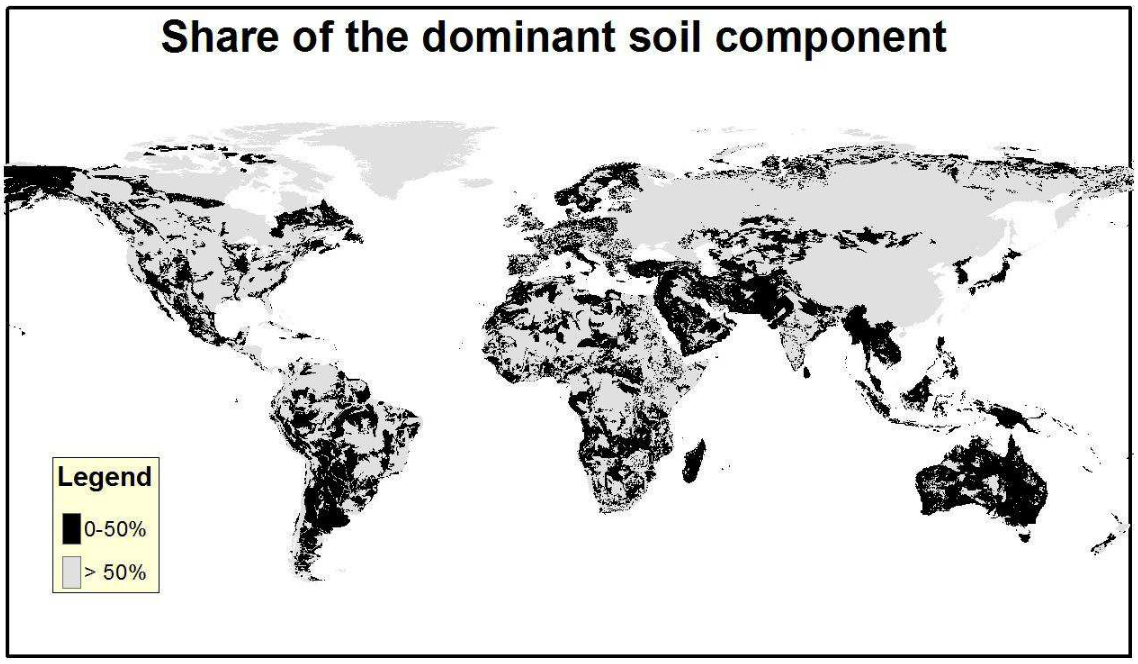


Figure 4. Analysis of shares and sequences of component soils. Grey areas represent soil mapping units where the share value of the dominant soil component holds more than 50%; Black areas are regions where the dominant soil component holds a share value of more than 50%

3.2 Determination of Crop Suitable Areas

While using the parameter value estimates of the dominant soil mapping units along with climate and terrain constraints, 9% of the earth's surface result in highly suitable (S1), 25% in suitable (S2) and 19% in marginally suitable (S3) areas (Figure 5). Barley (10.7%), wheat (5.6%), and oil palm (5.2%) are globally the most suitable crops (Figure 6) (Percentages of overall pixel, not of area).

While considering the parameter value estimates of all component soils in a given pixel, the area suitable for crop growth amounts to 54.5% of the earth's land surface excluding Antarctica. Roughly 4.5% can be categorised as highly suitable (S1); 27% and 23% can be classified as suitable (S2) and marginally suitable (S3), respectively (Figure 5). The most prominent crops were the same as when using dominant soils only, with adjustments in their overall percentages (barley-11.1%, wheat-6.5%, oil palm-5.9%) (Figure 6).

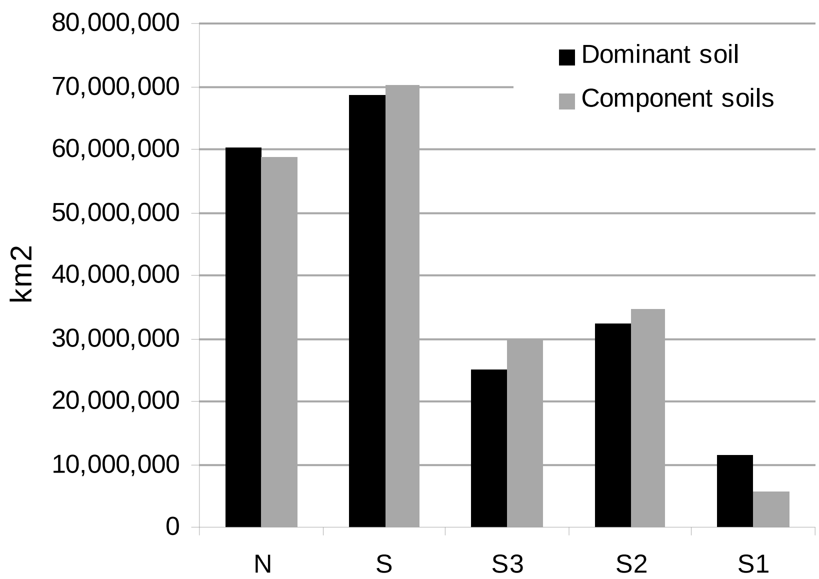
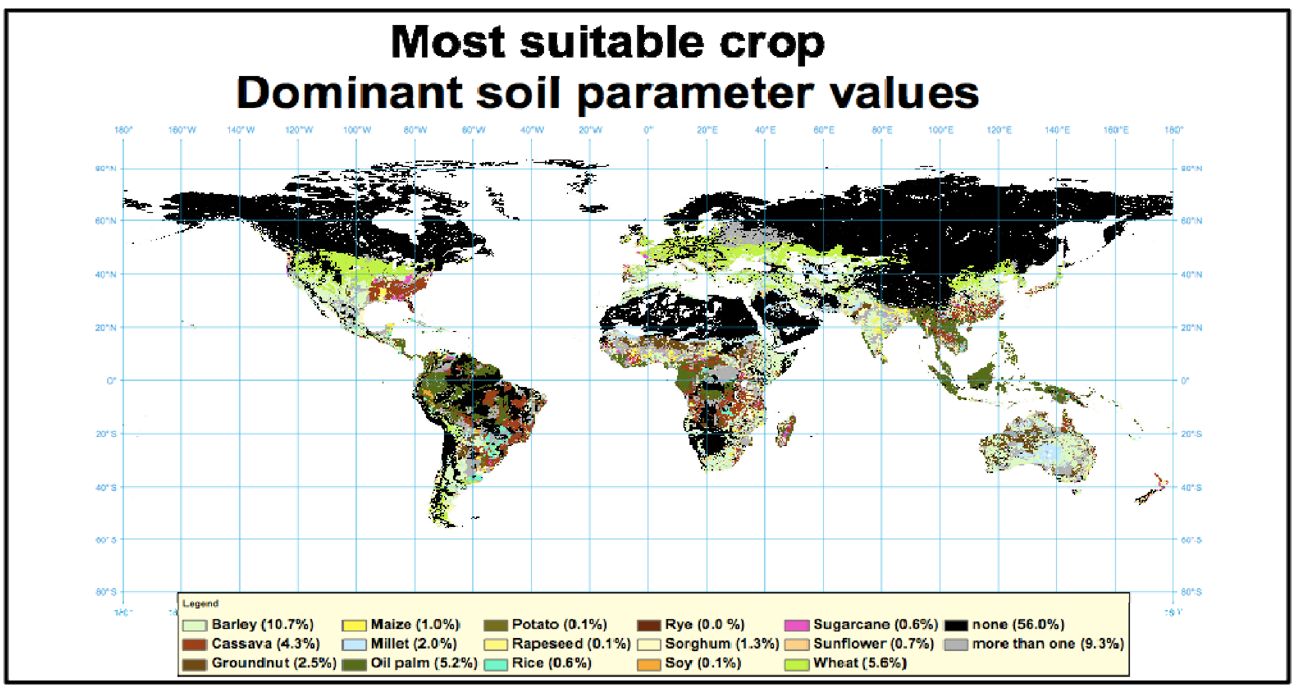
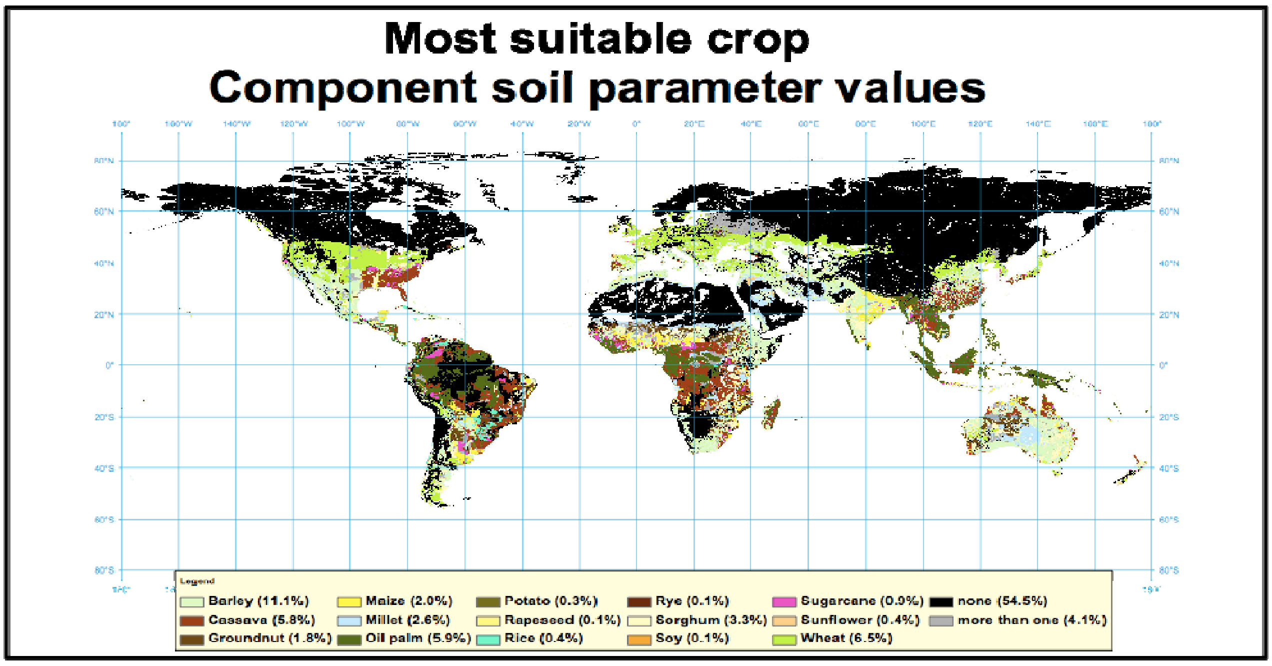


Figure 5 . Amount of c rop suitable areas while considering only dominant soil s (black bars) or all compon ent soils (grey bars). N– non suitable a reas; S–sum o f all suitable a reas; S3–mar ginally suitable; S2–suitable; S1–highly suitable



(a)



(b)

Figure 6. Distributio of the most suitable crop using all comp nent soil parameter value e timates (top) or dominant soils (bottom) (% values represent the relative amount of pixel for that crop, not the relative area)

4. Discussion

In about 1/3 of the soil mapping units the share value of the dominant soil is less than 50 % of the pixel. Its parameter value estimate, i.e. pH, salinity or organic carbon value, may not be the same as that of the weighted average of all component soils. In terms of crop suitability this translates in a 1 % increase of crop suitable areas of the earth's land surface when using all soil components of the soil mapping unit of the topsoil. The global distribution of crops itself is marginally affected - the ranking of the top 5 crops with the highest amount of pixels remains equal. Changes in the distribution of the suitability classes are important. For instance, in the highly suitable areas, a reduction of 4.3 % is observed when using component soils whereas the marginally suitable areas increased by 3.7 % (Figure 5).

The model results reflect the qualitative differences of the underlying databases. The HWSD is an integrated patchwork of diverse datasets (see Figure 1). South and Central America, East Africa and parts of Central Asia are fed with the SOTWIS data which have the latest updates of soil samples (latest version of 2006). Europe and Russia is based on the datasets of the European Soil Database, a very comprehensive set (FAO/IIASA/ISRIC/ISSCAS/JRC 2009b). North America, West Africa, and large parts of Asia and Australia are still based on the outdated Digital Soil Map of the World (DSMW). Data for China was produced by assigning one soil class per pixel. No changes in crop suitability classes occurred for those areas which are composed of only one, the dominant, component soil, such as in the case of China. Changes in crop suitability classes were in general more prominent where dominant soil shares are below 50 % such as in the Americas, Africa and Central Asia (Figure 7). For instance, while 867991 km^2 were assigned to be highly suitable when using the dominant soils in the Mercosur region (MRC), only 301704 km^2 were left in this category when using all component soils (Figure 7). Instead, 1300988 km^2 versus 1030206 km^2 were marginally suitable when using component soils or dominant soils only, respectively.

However, a linear relationship between data quality, more component soils and smaller share values in the dominant soils cannot be postulated. Some areas, in particular in the tropics, are predominantly composed of one dominant soil component with a share value of more than 50 % but are based on 'high quality' datasets (i.e. Amazon forest in Brazil based on SOTWIS, see grey areas in Figure 4). Other areas are based on 'low quality' datasets, such as Australia on DSMW, and show large areas with several component soils and dominant soil shares below 50 % (see black areas in Figure 4).

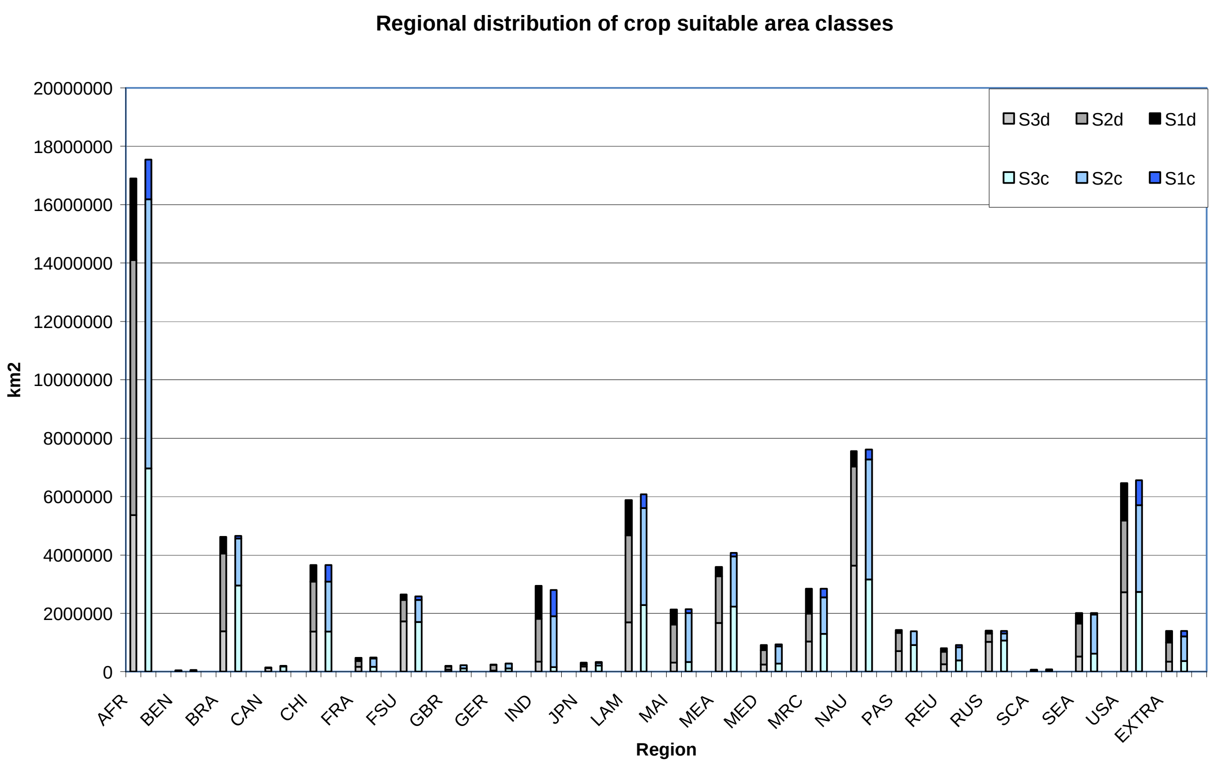


Figure 7. Region specific changes in crop suitability areas by categories using dominant soil parameter value estimates (d) or component soils (c). S3–marginally suitable, S2–suitable, S1–highly suitable

Now, how to make a choice of which dataset to use? The quality for all component soils is heterogenous; the effect on the extent and type of crop suitability minimal. The lack of consistent quality of global datasets is a known issue. A variety of research centres are working towards enhanced soil datasets and sampling, often in collaboration with many others such as in the Global Soil Initiative launched in 2011 (The Global Soil Partnership, 2011). In few cases of crop modelling some authors have undertaken extensive quality control of the underlying soil data and adapted it to their needs (Gijsman, Thornton, & Hoogenboom, 2007; Romero et al., 2012). This is very cumbersome and can only be carried out when sufficient expert staff is available for a specific target objective. However soil datasets are used widely by differing disciplines. We suggest explaining the inherent uncertainty attached to these datasets and lay open the error margin of their use. In this particular case, on the use of all component soils versus only the dominant soils we postulate that the error margin is of about 1% at a global scale.

It is clear to the authors that additional parameters can be used from the soil databases as well as a variety of other parameters such as refined climate datasets, in particular at the temporal scale. Knowledge on ethnicity, gender, management practices, adapted crops, irrigation, use of fertilizers and of the use of technology are all factors that influence the suitability of an area for agricultural purposes (FAO, 2007). Obtaining reliable data for these parameters may be even more challenging than for soil databases.

5. Conclusion

In this study, we intended to show the differences in model results when using all component soils for the analysis of crop suitability. This is important because it allows determining the level of uncertainty that modellers face when using current global soil databases. Including more parameters does not always mean better results. We showed that the distribution of the number of component soils of the HWSD is very heterogeneous on a geographical scale but is not linked to the quality of the underlying data subset. The error range for using either the dominant component soil versus all component soils could be considered to be 1%–the difference in crop suitable area between the two datasets. The margin of error varies according to the region and increases to up to 4% when looking at the individual suitability classes.

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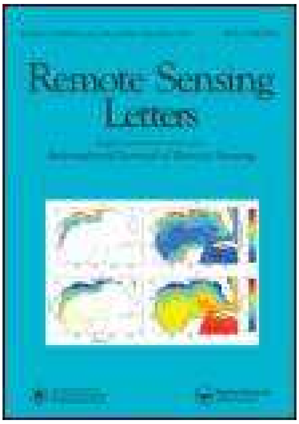

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Are urban areas endangering the availability of rainfed crop suitable land?

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Are urban areas endangering the availability of rainfed crop suitable land?

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Many concerns have been raised about urban sprawl and the subsequent disappearance of agricultural land. Regulations have been put in place to reduce urban sprawl and protect agricultural areas in many countries, but how much potentially crop suitable land really is endangered by urban areas on a global scale has not been addressed so far. In this study, we compare the extent of urban areas as pro-duced by the Center for Sustainability and the Global Environment, Madison, WI, USA, with a map of potential crop suitable areas produced by us. We show that, of the postulated 0.5% of the Earth's surface currently covered by urban areas, Asia, Europe and North America take away the largest shares and that 1% of the globally available highly crop suitable areas are currently taken up by cities, with Japan and California being extreme examples of up to 15% of highly suitable areas covered with cities.

1. Introduction

Historically, urban areas mostly developed at strategically important points and where the necessary resources to survive were present, which was often in fertile and rich soil regions of river deltas, oasis or at the edges of lakes with favourable climates. Imhoff *et al*. (2004) showed that in the United States approximately 3% of the land surface is taken up by urban land and 15% of the best agricultural lands of California have been transformed into urban areas. Spilková and Sefrna (2010) pointed out that 44% of the land dedicated to a new retail area around Prague was made up of high-quality soils (chernozems and luvisols). In the Beijing–Tianjin–Hebei urban conglomeration in China, about 74% of the current urban area was converted from former agricultural land in the decade of the 1990s (Tan *et al*. 2005). In the surroundings of the town of Saharanpur in India, about 48% of the agricultural land was lost to urbanization in the 1990s of which about one-third were of high quality (Fazal 2001). Globally, nonetheless, approximately 12% of the Earth's land surface excluding Antarctica is used as cropland (Ramankutty *et al*. 2008), whereas only about 0.5–3% is made up of urban areas, depending on the study (Schneider *et al*. 2010).

Many countries see a problem in the reduction of available agricultural land due to its conversion into urban areas, industrial sites, roads and other impervious surfaces, which, in most cases, is irreversible. They have thus implemented legislative measures

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to reduce expansion. This has been the case in the developed world as well as in the developing countries and was even addressed by the British during the Second World War (Stamp 1941). Many studies focus on the effects of these measures on urban sprawl and their impact on agricultural land, be it in North America (Schwartz and Hansen 1975, Cocklin *et al*. 1983, Krushelnicki and Bell 1989, Brabec and Smith 2002, Irwin and Bockstael 2004, Wu and Cho 2007, Thompson and Prokopy 2009), Europe (Reidsma *et al*. 2006, Spilková and Sefrna 2010, Gant *et al*. 2011), China (Chen 2007, Yaping and Min 2009) or the developing countries in general (Lenney *et al*. 1996, Thomlinson and Rivera 2000, Hara *et al*. 2005, Braimoh and Onishi 2007, Thapa and Murayama 2008, Firman 2009). The verdict on the use of regulation of urban sprawl is rather pessimistic as only in few cases agricultural land was safeguarded (Luzar 1988). Positive examples are, for instance, Japan where 30% of the land surfaces are made up of urban areas, but agricultural land conservation methods are extremely strict and have led to an effective retention of agricultural lands (Sorensen 2000). Also in the Nile Delta area of Egypt, only 0.4% of high-valued agricultural land has been lost to urbanization in the decade of the 1980s (Lenney *et al*. 1996).

All current studies focus on distinct urban agglomerations or national regulations using Geographic Information System (GIS) techniques and satellite image analysis in order to track the changes in land use, but globally the loss of agricultural land due to urban areas is rather unknown. In this study, we want to show the global extent of urban areas and their expansion on areas of potentially high crop suitability, to under-stand the dimension of the loss of potential food production. For this purpose, we used a data set of urban extent produced on the basis of remote sensing in combination with a map of potential crop suitable areas fashioned on the basis of fuzzy logic modelling.

2. Materials and methods

2.1 *Maps*

We used the urban area map as produced by Schneider *et al*. (2010), which is based on 500 m Moderate Resolution Imaging Spectroradiometer (MODIS) data and has shown extremely good validation results (r^2 = 0.90) for 140 cities.

The areas of potential crop suitability were produced on the basis of a fuzzy logic approach integrating soil, terrain and climate constraints of 15 globally relevant food crops (see also Avellan *et al*. submitted August 2011, in review September 2011). We first assigned growth likelihood curves to each plant for each parameter, which were obtained from Sys *et al*. (1993), and then determined the limiting parameter for each plant (as the minimum likelihood across all parameters for each plant), to subse-quently gain knowledge about the most suited plant (maximum likelihood across all plants) for each 5 arc-minute pixel on the Earth's land surface excluding Antarctica (Burrough *et al*. 1992). Areas that did not reach the threshold of more than 0.4 (includ-ing) in minimum likelihood across all parameters were said to be non-suitable areas for agriculture following the assigned likelihood criteria determined by Sys *et al*. (1993); areas with suitabilities larger than 0.4 and up to 0.6 (including) were marginally suit-able, areas with suitabilities larger than 0.6 and up to 0.8 (including) were said to be suitable and areas with suitabilities larger than 0.8 and up to 1.0 (including) were highly suitable (according to FAO crop suitability classification (FAO 1976)).

We compared our crop suitability results with current crop growth areas of wheat, maize and rice as determined by Ramankutty *et al*. (2008) and obtained a 70% overlap

(Avellan *et al*. submitted August 2011, in review September 2011). A few caveats exist in our current map of potential agricultural areas and need to be kept in mind: (a) since we only considered natural rainfall for this study, agricultural areas that are dependent on irrigation are not considered here; (b) we know that the winter wheat area of the Canadian wheat belt does not appear in our model as annual mean temperature is too low to allow wheat growth there under our current parameterization; and (c) the Australian desert region is crop suitable as winter precipitations in this area increase annual cumulative rainfall and thus make crop growth possible.

2.2 *Comparison*

The urban areas map was first re-sampled to match the grid cell extent of the crop suitable areas map (0.0083333 arc degrees or roughly 1 km^2 at the equator). After reclassifying the crop suitable areas map, we subtracted the urban areas map from the crop suitability map. This procedure results in a data set that shows the distinc-tion between the relative area of crop suitable land covered by urban areas and the relative amount of crop suitable land not covered by them. Continents, countries and states were defined according to the Global Administrative Areas, which are the standard outlines as provided by ESRI's ArcGIS, and the percentages were extracted accordingly.

We looked at the following three aspects:

1. the distribution of crop suitable areas (highly suitable–non-suitable) per region or continent (number of pixels per suitability category divided by the total number of pixels of the Earth's land surface – excluding Antarctica);
2. the relative distribution of urban areas within the crop suitable areas of each region (number of pixels in urban areas per suitability category divided by the total number of pixels in urban areas); and
3. the area covered by urban areas either in relation to the global land surface (number of pixels in urban areas per region divided by the total number of pixels in urban areas globally), or within each suitability class of each region (number of pixels in urban areas per region per suitability category divided by the total number of pixels per suitability category regionally).

3. Results

Globally, about 44% of the Earth's land surface is suitable for crop growth, with, however, only 7% highly crop suitable land (table 1). Both Africa and South America achieve more than 60% of their land surface to be suitable for crop growth with 12% and 10% of highly crop suitable areas, respectively. Asia, North America and Europe only achieve around 30% of their land mass to be crop suitable with 6% or less of highly crop suitable areas. Australia is an exception in our results, as mentioned above, resulting in 98% crop suitable land within their territory of which 66%, however, is only marginally suitable for crop growth.

Our results further show that cities are in quite a few cases built on or around fertile areas. Although, according to the data, only 0.5% of the global land surface is cov-ered with urban areas, 80% of the cities extents fall into the category of crop suitable land with 19% of the cities extents covering highly crop suitable areas (table 2). Asia covers the largest amount of global land surface with urban areas (0.16%) followed by North America and Europe (0.10% each) (figure 1(*a*)). Although urban land surfaces

Table 1. Relative distribution of Earth's land surface areas per crop suitability per continent and globally.

	Africa	Asia	Australia	Europe	North America	South America	Global
Highly suitable (%)	12	6	10	3	6	10	7
Suitable (%)	22	10	21	17	11	23	15
Marginally suitable (%)	30	16	66	19	11	34	22
Sum suitable (%)	63	32	98	39	27	67	44
Non-suitable (%)	37	68	2	61	73	33	56

Table 2. Relative distribution of urban areas per crop suitability per continent and globally.

	Africa	Asia	Australia	Europe	North America	South America	Global
Highly suitable (%)	14	28	7	6	22	12	19
Suitable (%)	38	29	20	43	33	42	35
Marginally suitable (%)	30	24	61	30	23	25	26
Sum suitable (%)	82	81	88	79	78	80	80
Non-suitable (%)	18	19	12	21	22	20	20

of Japan and California only roughly make up 0.010% each of the global land surface, they cover more than 13% of their highly suitable areas with cities and thus even top off Asia, Europe and North America which roughly cover 2% of their highly suitable areas with cities (figure 1(*b*)). The city of Los Angeles is a dramatic example of an urban area that has covered most, if not all, of its closely available highly crop suitable areas (figure 2).

4. Discussion

Our results show that although urban areas may not take up too much actual land of the Earth's land surface, they are extensively placed on the crop suitable areas of our planet. We have so far globally lost 1% of our most suitable areas to cities. In some extreme situations, up to 15% of the available crop suitable areas have been taken up by cities as is the case in California and Japan, which are values comparable to the literature (Sorensen 2000, Imhoff *et al*. 2004).

The caveats in our crop suitable areas affect mainly the results of urban areas within irrigated areas, such as Cairo which is not considered in our case as a city within crop suitable land. The problems with the underestimation of crop suitable land in Canada do not strongly affect our results as the amount and extent of urban areas within the Canadian wheat belt is rather low. Conversely, the overestimation of crop suitable land within Australia also does not largely alter our results as most of Australia is marginally suitable and cities mainly fall into the areas of suitable or highly suitable land of the eastern Australian coast.

Assuming that both Africa and South America attain high urbanization degrees similar to those in Europe, we could attain global urban areas of roughly 0.8% of the Earth's land surface, almost double the current amount estimated here. Globally, we would thus further lose another 1% of highly suitable land. Africa's urban areas

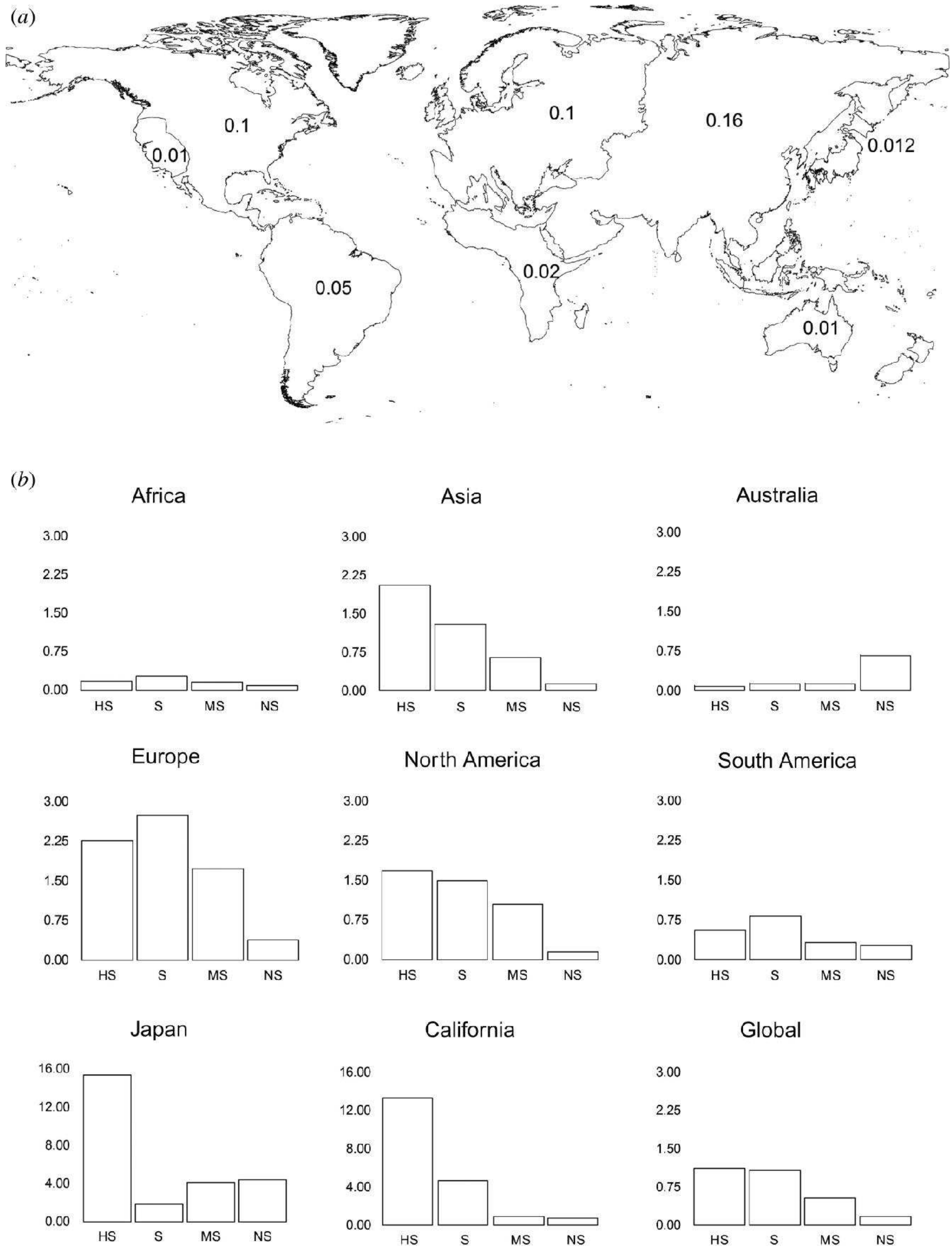

Figure 1. Distribution of cities and crop suitable areas (*a*) Global map showing the dis-torted relative global land surfaces covered by urban areas per continent/country/state after data by Schneider *et al*. (2009) (number in continents countries denotes percentage); (*b*) Percentage of crop growth suitable areas covered by urban areas per suitability category and continent/country/state. *y*-Axis represents the percentage of area covered – note that *y*-axis maximum is higher for Japan and California than in all other graphs; *x*-axis from left to right: HS – highly suitable, S – suitable, MS – marginally suitable and NS – non-suitable area.

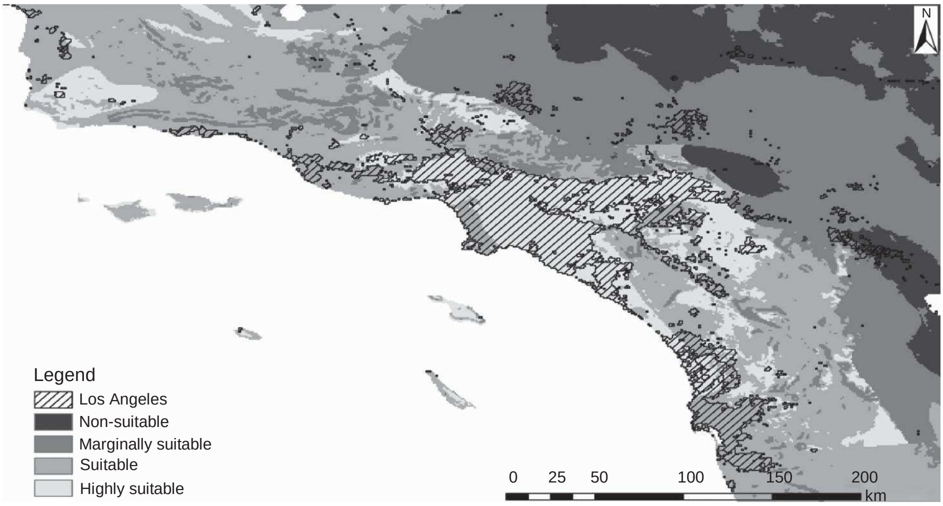

Figure 2. Extent covered by Greater Los Angeles and its coverage by the different suitability categories, showing that large extents of the city cover areas of high suitability.

would then make up 0.25% of all Earth's surface and would then cover almost 1.5% of the continents' crop suitable land, 11 times the current amount. South America would triple both the proportion of the Earth's surface taken up by its urban areas (to 0.17%) and the proportion of its own crop suitable land occupied by these areas (to 1.5%).

The amount of crop suitable areas remains rather large when using the conservative estimates of Schneider *et al*. (2009) as used here. Hence, globally, currently 99.2% of the crop suitable areas are not covered by cities. Uncertainties in determining urban areas remain large, especially when looking at urban fringes, rural urban areas and urban sprawl along the side of the roads, which is especially true for the develop-ing countries (Schneider *et al*. 2010). Estimates based on other data sets such as the Global Rural-Urban Mapping Project (GRUMP), which approximates substantially more than what we assumed in this study, namely 3% of the Earth's surface to be covered by urban areas, may render different results and could be the target of future studies (CIESIN *et al*. 2004). Current cropland cover only makes use of about half of the crop suitable areas, mostly the highly suitable and suitable areas (own calculations based on GlobCover 2009 extent of rainfed agriculture). Protected areas cover more than 12% of the globally available crop suitable areas and wetlands cover roughly 1.3% (own calculations based on International Union for Conservation of Nature (IUCN) protected areas map and GlobCover 2009 extent of wetlands). Thus, the expansion of cities will most likely not necessarily affect the amount of agricultural land but will cause the reduction of other ecosystems currently covering potentially crop suitable areas as has been occurring in the past.

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Annex

Annex 1: Soil classification according to FAO 1974

G **GLEYSOLS**

Ge Eutric Gleysols
Gc Calcaric Gleysols
Gd Dystric Gleysols
Gm Mollic Gleysols
Gh Humic Gleysols
Gp Plinthic Gleysols
Gx Gelic Gleysols

R **REGOSOLS**

Re Eutric Regosols
Rc Calcaric Regosols
Rd Dystric Regosols
Rx Gelic Regosols

I **LITHOSOLS**

Q **ARENOSOLS**

Qc Cambic Arenosols
All Luvic Arenosols
If Ferralic Arenosols
A Albic Arenosols

E **RENDZINAS**

U **RANKERS**

T **ANDOSOLS**

To Ochric Andosols
Tm Mollic Andosols
Th Humic Andolsols
Tv Vitric Andosols

V **VERTISOLS**

Vp Pellic Vertisols
Vc Chromic Vertisols

Z **SOLONCHAKS**

Zo Orthic Solonchaks
Zm Mollic Solonchaks
Zt Takyric Solonchaks
Zg Gleyic Solonchaks

S **SOLONETZ**

So Orthic Solonetz
Sm Mollic Solonetz
Sg Gleyic Solonetz

Y **YERMOSOLS**

Yh Haplic Yermosols
Yk Calcic Yermosols
Yy Gypsic Yermosols
Yl Luvic Yermosols
Yt Takyric Yermosols

X **XEROSOLS**

Xh Haplic Xerosols
Xk Calcic Xerosols
Xy Gypsic Xerosols
Xl Luvic Xerosols

K **KASTANOZEMS**

KHz Haplic Kastanozems
Koki Calcic Kastanozems
Kl Luvic Kastanozems

C **CHERNOZEMS**

Ch Haplic Chernozems
Ck Calcic Chernozems
Cl Luvic Chernozems
Cg Glossic Chernozems

H **PHAEOZEMS**

Hh Haplic Phaeozems
Hc Calcaric Phaeozems
Hl Luvic Phaeozems
Hg Gleyic Phaeozems

M **GREYZEMS**

Mo Orthic Greyzems
Mg Gleyic Greyzems

B **CAMBISOLS**

Be Eutric Cambisols
Bd Dystric Cambisols
Bh Humic Cambisols
Bx Gelic Cambisols
Bk Calcic Cambisols
Bc Chromic Cambisols
Bv Vertic Cambisols
Bf Ferralic Cambisols

L **LUVISOLS**

Lo Orthic Luvisols
Lc Chromic Luvisols
Lk Calcic Luvisols
Lv Vertic Luvisols
Lf Ferric Luvisols
La Albic Luvisols
Lap Plinthic Luvisols
Lag Gleyic Luvisols

D **PODZOLUVISOLS**

De Eutric Podzoluvisols
Dd Dystric Podzoluvisols
Dg Gleyic Podzoluvisols

P **PODZOLS**

Po Orthic Podzols
Pl Luvic Podzols
Pf Ferric Podzols
Ph Humic Podzols
Pp Placic Podzols
Pg Gleyic Podzols

W **PLANOSOLS**

We Eutric Planosols
Wd Dystric Planosols
Wm Mollic Planosols
Wh Humic Planosols
Ws Solodic Planosols
Wx Gelic Planosols

A **ACRISOLS**

Ao Orthic Acrisols
Af Ferric Acrisols
Ah Humic Acrisols
Ap Plinthic Acrisols
Ag Gleyic Acrisols

N **NITOSOLS**

Ne Eutric Nitosols
Nd Dystric Nitosols
Nh Humic Nitosols

F **FERRALSOLS**

Fo Orthic Ferralsols
Fx Xantic Ferralsols
Fr Rhodic Ferralsols
Fahd Humic Ferralsols
Far Acrid Ferralsols
Fop Plinthic Acrisols

O **HISTOSOLS**

Oe Eutric Histosols
Od Dystric Histosols
Ox Gelic Histosols

J **FLUVISOLS**

Je Eutric Fluvisols
Jc Calcaric Fluvisols
Jd Dystric Fluvisols
Jt Thionic Fluvisols

Annex 2: Soil classification according to FAO 1990

FL	FLUVISOLS
FLe	Eutric Fluvisols
FLc	Calcaric Fluvisols
FLd	Dystric Fluvisols
FLm	Mollic Fluvisols
FLu	Umbric Fluvisols
FLt	Thionic Fluvisols
FLs	Salic Fluvisols

GL	GLEYSOLS
GLe	Eutric Gleysols
GLk	Calcic Gleysols
GLd	Dystric Gleysols
GLa	Andic Gleysols
GLm	Mollic Gleysols
GLu	Umbric Gleysols
GLt	Thionic Gleysols
GLi	Gelic Gleysols

RG	REGOSOLS
RGe	Eutric Regosols
RGc	Calcaric Regosols
RGy	Gypsic Regosols
RGd	Dystric Regosols
RGu	Umbric Regosols
RGi	Gelic Regosols

LP	LEPTOSOLS
LPe	Eutric Leptosols
LPd	Dystric Leptosols
LPk	Rendzic Leptosols
LPm	Mollic Leptosols
LPu	Umbric Leptosols
LPq	Lithic Leptosols
LPi	Gelic Leptosols

AR	ARENOSOLS
ARh	Haplic Arenosols
ARb	Cambic Arenosols
ARl	Luvic Arenosols
ARo	Ferralic Arenosols
ARa	Albic Arenosols
ARc	Calcaric Arenosols
ARg	Gleyic Arenosols

AN	ANDOSOLS
ANh	Haplic Andosols
ANm	Mollic Andosols
ANu	Umbric Andosols
ANz	Vitric Andosols
ANg	Gleyic Andosols
ANi	Gelic Andosols

VR	VERTISOLS
VRe	Eutric Vertisols
VRd	Dystric Vertisols
VRk	Calcic Vertisols
VRy	Gypsic Vertisols

CM	CAMBISOLS
CMe	Eutric Cambisols
CMd	Dystric Cambisols
CMu	Humic Cambisols
CMc	Calcaric Cambisols
CMx	Chromic Cambisols
CMv	Vertic Cambisols
CMo	Ferralic Cambisols
CMg	Gleyic Cambisols
CMi	Gelic Cambisols

CL	CALCISOLS
CLh	Haplic Calcisols
CLl	Luvic Calcisols
Clp	Petric Calcisols

GY	GYPSISOLS
GYh	Haplic Gypsisols
GYk	Calcic Gypsisols
GYl	Luvic Gypsisols
GYp	Petric Gypsisols

SN	SOLONETZ
SNh	Haplic Solonetz
SNm	Mollic Solonetz
SNk	Calcic Solonetz
SNy	Gypsic Solonetz
SNj	Stagnic Solonetz
SNg	Gleyic Solonetz

SC	SOLONCHAKS
SCh	Haplic Solonchaks
SCm	Mollic Solonchaks
SCk	Calcic Solonchaks
SCy	Gypsic Solonchaks
SCn	Sodic Solonchaks
SCg	Gleyic Solonchaks
SCi	Gelic Solonchaks

KS	**KASTANOZEMS**
KSh	Haplic Kastanozems
KSl	Luvic Kastanozems
KSk	Calcic Kastanozems
KSy	Gypsic Kastanozems

CH	**CHERNOZEMS**
CHh	Haplic Chernozems
CHk	Calcic Chernozems
CHl	Luvic Chernozems
CHw	Glossic Chernozems
CHg	Gleyic Chernozems

PH	**PHAEOZEMS**
PHh	Haplic Phaeozems
PHc	Calcaric Phaeozems
PHl	Luvic Phaeozems
PHj	Stagnic Phaeozems
PHg	Gleyic Phaeozems

GR	**GREYZEMS**
GRh	Haplic Greyzems
GRg	Gleyic Greyzems

LV	**LUVISOLS**
LVh	Haplic Luvisols
LVf	Ferric Luvisols
LVx	Chromic Luvisols
LVk	Calcic Luvisols
LVv	Vertic Luvisols
LVa	Albic Luvisols
LVj	Stagnic Luvisols
LVg	Gleyic Luvisols

PL	**PLANOSOLS**
PLe	Eutric Planosols
PLd	Dystric Planosols
PLm	Mollic Planosols
PLu	Umbric Planosols
PLi	Gelic Planosols

PD	**PODZOLUVISOLS**
PDe	Eutric Podzoluvisols
PDd	Dystric Podzoluvisols
PDj	Stagnic Podzoluvisols
PDg	Gleyic Podzoluvisols
PDi	Gelic Podzoluvisols

PZ	**PODZOLS**
PZh	Haplic Podzols
PZb	Cambic Podzols
PZf	Ferric Podzols
PZc	Carbic Podzols
PZg	Gleyic Podzols
PZi	Gelic Podzols

LX	**LIXISOLS**
LXh	Haplic Lixisols
LXf	Ferric Lixisols
LXp	Plinthic Lixisols
LXa	Albic Lixisols
LXj	Stagnic Lixisols
LXg	Gleyic Lixisols

AC	**ACRISOLS**
ACh	Haplic Acrisols
ACf	Ferric Acrisols
ACu	Humic Acrisols
ACp	Plinthic Acrisols
ACg	Gleyic Acrisols

AL	**ALISOLS**
ALh	Haplic Alisols
ALf	Ferric Alisols
ALu	Humic Alisols
ALp	Plinthic Alisols
ALj	Stagnic Alisols
ALg	Gleyic Alisols

NT	**NITISOLS**
NTh	Haplic Nitisols
NTr	Rhodic Nitisols
NTu	Humic Nitisols

FR	**FERRALSOLS**
FRh	Haplic Ferralsols
FRx	Xanthic Ferralsols
FRr	Rhodic Ferralsols
FRu	Humic Ferralsols
FRg	Geric Ferralsols
FRp	Plinthic Ferralsols

PT	**PLINTHOSOLS**
PTe	Eutric Plinthosols
PTd	Dystric Plinthosols
PTu	Humic Plinthosols
PTa	Albic Plinthosols

HS	**HISTOSOLS**
HSl	Folic Histosols
HSs	Terric Histosols
HSf	Fibric Histosols
HSt	Thionic Histosols
HSi	Gelic Histosols

AT	**ANTHROSOLS**
ATa	Aric Anthrosols
ATc	Cumulic Anthrosols
ATf	Fimic Anthrosols
ATu	Urbic Anthrosols

Annex 3: Globcover classification legend

Value	Global Globcover legend (level 1)	
11	Post-flooding or irrigated croplands	
14	Rainfed croplands	
20	Mosaic Cropland (50-70%) / Vegetation (grassland, shrubland, forest) (20-50%)	
30	Mosaic Vegetation (grassland, shrubland, forest) (50-70%) / Cropland (20-50%)	
40	Closed to open (>15%) broadleaved evergreen and/or semi-deciduous forest (>5m)	
50	Closed (>40%) broadleaved deciduous forest (>5m)	
60	Open (15-40%) broadleaved deciduous forest (>5m)	
70	Closed (>40%) needleleaved evergreen forest (>5m)	
90	Open (15-40%) needleleaved deciduous or evergreen forest (>5m)	
100	Closed to open (>15%) mixed broadleaved and needleleaved forest (>5m)	
110	Mosaic Forest/Shrubland (50-70%) / Grassland (20-50%)	
120	Mosaic Grassland (50-70%) / Forest/Shrubland (20-50%)	
130	Closed to open (>15%) shrubland (<5m)	
140	Closed to open (>15%) grassland	
150	Sparse (>15%) vegetation (woody vegetation, shrubs, grassland)	
160	Closed (>40%) broadleaved forest regularly flooded - Fresh water	
170	Closed (>40%) broadleaved semi-deciduous and/or evergreen forest regularly flooded - Saline water	
180	Closed to open (>15%) vegetation (grassland, shrubland, woody vegetation) on regularly flooded or waterlogged soil - Fresh, brackish or saline water	
190	Artificial surfaces and associated areas (urban areas >50%)	
200	Bare areas	
210	Water bodies	
220	Permanent snow and ice	