IMPACTS OF CLIMATE CHANGE ON
GLOBAL AGRICULTURAL LAND AVAILABILITY

BY

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THESIS

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Abstract

This thesis uses several global databases, including soil properties, slope, temperature and precipitation to simulate agricultural land suitability under both current and projected climate from thirteen general circulation models (GCMs) and two emission scenarios, A1B & B1, which represent relatively high and low emission, respectively. Two ensemble methods, Simple Average Method (SAM) and Root Mean Square Error Ensemble Method (RMSEMM), are employed to assemble the regional climate change which attempts to abate the uncertainty involved in global GCM projections. Fuzzy logic, which handles land classification in an approximate yet efficient way, is adopted to estimate the land suitability through empirically determined membership functions of soil properties, slope, air temperature and Humidity Index, and fuzzy rules chosen through a learning process based on remote sensed crop land products. Land suitability under five scenarios, which are the baseline scenario with the present climate and four climate change projections, A1B-SAM, A1B-RMSEMM, B1-SAM, and B1-RMSEMM, is assessed for both global and seven important agricultural regions in the world. The change patterns of climatic factors and land suitability are explored and analyzed. It is found that countries at the high latitudes of north hemisphere are more likely to benefit from climate change, while countries at mid- and low latitudes may suffer different levels of loss of potential arable land. Expansions of the gross potential arable land are likely to occur in regions at the north high latitudes, like Russia, North China and U.S., while shrinking can be expected in South America, Africa, India and Europe. Although the greatest potential for agricultural expansion lies in Africa and South America, with current cultivated land accounting for approximately 20% of the net potential arable land in the world, negative effect from climate change may decline the potential. In summary, climate change is likely to alter the global distribution of potential arable land and further influence agricultural related socio-economic aspects by the end of this century.
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CHAPTER 1
INTRODUCTION

Climate change due to enhanced greenhouse effect and its possible impacts on future agricultural production have raised a lot of concerns. It posts greater threats than ever by combining reverse effects of increasing population, higher temperature, less available water in most needed regions, and more intense and frequent extreme events (WFP et al., 2009). The magnitudes of the impacts vary by region, time, and most importantly, the socio-economic development path (Schmidhuber and Tubiello, 2007). All of the four dimensions of food security will be challenged: food availability, food accessibility, food utilization and food systems stability (FAO, 2008). More people will be at risk of hunger due to climate change, especially for the poor people in less developed countries, whose lives depend directly on agriculture (Ludi, 2009). Although many obstacles exist, like the uncertainties involved in climate change, economic development paths and policies, studies and adaptations are necessary to figure out the most vulnerable regions and mitigate possible negative influences. Many studies have been undertaken to explore climate change impacts on crop yield (Parry et al., 1999; Long et al., 2006; Li et al., 2009; Muller et al., 2010), while only a few studies have explored the impacts on global agricultural land availability (Cramer and Solomon, 1993; Ramankutty, 2002). Since food production depends directly on the available agricultural lands, it is of significant value to access the potential arable land availability and examine its climate-induced changes in the future.

1.1. CLIMATE CHANGE

Climate change has been a socially and scientifically significant issue in the past few decades. The observed global temperature has increased linearly at a rate of 0.76 Celsius in the past 100-year (1906-2005), and the pace has doubled between 1956 to 2005 (IPCC, 2007a). Temperature records from multiple sources have proven this increasing trend, as shown in Figure 1.1. This warming phenomenon is related to the rapid increase in anthropogenic greenhouse gas (GHG) emissions in the last century. In the mean time, the global sea surface has risen at an average rate of 1.8 (1.3 to 2.3) mm per year over 1961 to 2003 and at an average rate of about 3.1 (2.4 to 3.8) mm
per year from 1993 to 2003 (IPCC, 2007a), mainly due to the melting of glaciers. Observational evidence has been found all around the world, showing that the climate is changing in a way that is more than just natural oscillation.

Unfortunately, this warming trend has high confidence to continue. By the end of the 21st century, according to the IPCC (Figure 1.2), greenhouse gas emissions might cause the mean global temperature to rise by another 0.6-4.0 Celsius (IPCC, 2007a). Projected warming is likely to have greatest impacts on lands at most high northern latitudes, and least over the Southern Ocean (near Antarctica) and northern North Atlantic (IPCC, 2007a).

Changes in precipitation and temperature modify the evaporation and soil moisture storage (Olesen and Bindi, 2002), leading to alterations in runoff and other components of hydrological systems. By 2050, north high latitudes and some wet tropical areas have high possibility to experience increases of runoff by 10 to 40%, while some dry regions at mid-latitudes and dry tropics may expect decreases by 10 to 30%, due to less rainfall and more evapotranspiration (IPCC, 2007a). Furthermore, extreme events, like floods and droughts, are likely to be more intense and frequent.

Consequently, the changes in temperature and water will have significant impacts on the agricultural processes, and further economic system and policies. Therefore, it is of great value to explore the possible impacts of climate change on global agriculture, so that measures and adaptation can be implemented to prevent or mitigate possible negative effects.

1.1.1. Climate change variability

Climate changes vary significantly at both the spatial and the temporal scale. Spatially, the temperature increase was greater at higher northern latitudes. During the period from 1900 to 2005, the most significant precipitation increases occurred in eastern parts of North and South America, northern Europe and northern and central Asia, whereas severe declines were experienced in initially arid regions, like Sahel, the Mediterranean, and southern Africa (IPCC, 2007a). Temporally, the temperature increase is more apparent in the winter season and less severe during the summer. In addition, precipitation is also likely to change as a component of the changed
hydrological system. Consequently, the impacts will vary significantly with location and time. Therefore, it is necessary to take both the spatial and temporal variability into consideration when trying to estimate the effects of climate change.

To achieve more accurate information of regional climate, downscaling has been widely used to explore its impacts on hydrological processes and basin water resources management (Xu, 1999; Wilby et al., 2002a; Wilby et al., 2002b). It consists of two main categories: dynamical downscaling, which bases on the modeling of physical climate processes and usually involves the development of regional climate model (RCM), and statistical downscaling, which relies on the empirical relationship derived from observational data between large-scale climate parameters and local values (Xu, 1999; Wigley et al., 1990; Nguyen, 2005). This work focuses on the global pattern and trend, and the regional variability is not taken into account. Another issue worth noticing is that the variability discussed here is different from the natural climate variability. Although natural variability can induce impact noise (Hulme et al., 1999), it is not considered in this study.

1.1.2. Climate change uncertainty

Climate change is also subject to great uncertainty due to the simulation models and directions of socio-econ development. Globally, more than 20 General Circulation Models (GCMs) have been developed to simulate and predict possible climate change. Although these models converge acceptably at the global scale, the outcomes at the regional scale vary a lot, and some models even conflict with each other (Laurent and Cai, 2007). Such regional uncertainty arises from two main factors: (1) different models adopt different climate sensitivities, ranging from 2.1(PCM) to 4.4 (UKMO-HadGEM1) Celsius (IPCC, 2007b), and their distributions differ from those estimated from observational data (Knutti et al., 2008); (2) combinations of forcings and the quantification methods of the common forcings vary by models (Collins et al., 2006; Forster and Taylor, 2006). Therefore, climate prediction from a single GCM is deficient due to its limitations within the assumptions, no matter how sophisticated the model is. Only large ensembles sampling the widest range of possible outcomes can provide a reliable view into the future (Murphy et al., 2004).
To combine the results of different GCMs, simple average method (SAM) has been used a lot and many researches have shown that the simulation skill of the average can be superior to any of the individual models (Connolley and Bracegirdle), yet one underlying drawback is that SAM fails to consider the variations in quality between models (Murphy et al., 2004). At the same time, root mean square error minimization method (RMSEMM) was also popular as a tool to determine the probability distribution for a selected set of GCMs (Laurent and Cai, 2007). In their study, the best combination of GCMs was targeted rather than the combination of the best GCMs. However, the RMSEMM depends entirely on the quality of the historical data which may include considerable errors and uncertainty. To reduce the amount of uncertainty of SAM and RMSEMM resulting from the limitations in their assumptions, I will adopt these two methods as a comparison to provide a more comprehensive and reliable insight into the potential climate change impacts.

In addition, the future socio-econ development paths are also unknown. IPCC assumed 6 emission scenarios in their Fourth Assessment Report: A1F1, A1T, A1B, B1, A2 and B2. Due to the data availability and simulation requirements, scenario A1B and B1 are chosen in this study. The A1B emission scenario assumes a future world of rapid economic growth, low population growth and rapid introduction of more efficient technology, while the B1 emission scenario assumes a convergent world with the same global population as in the A1 storyline but with rapid changes in economic structures toward a more “green” economy (IPCC, 2009). In other words, the A1B scenario emits more GHGs than B1, and is likely to cause higher temperature increases at the end of this century. With these two emission scenarios as comparison, I hope to achieve a broader view of the possible impacts in the future, plus, a reasonable range of what is likely to happen, as a valuable reference for researchers and policy makers.

1.2. POSSIBLE AGRICULTURAL IMPACTS

Possible impacts of climate change on world food production have raised a lot of concerns. The resulting effects depend on current climatic and soil conditions, the direction of the changes, and the availability of resources & infrastructures to cope
with changes (Olesen and Bindi, 2002). Hence, climate change is expected to affect agriculture variously around the globe (Parry et al., 1999). Agriculture on the west coast of the US, which depends on the melted runoff from the Rocky Mountains during Spring may have to adapt if the warming causes early spring rainfall, whereas East Asia and the Pacific Rim are expected to receive less precipitation due to growing El Niño events (Hopkin, 2005). Developing countries in the tropical and subtropical regions are the most vulnerable to the potential impacts and very likely to bear the brunt of them. Therefore, a more comprehensive understanding of the impacts is essential to avoid the potential disasters and mitigate the negative effects.

1.2.1. Food security

According to the definition at the World Food Summit (WFS) in November 1996, Food security exists when “all people at all times have physical or economic access to sufficient safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life” (FAO, 1996). According to Parry et al. (1999)’s study, the additional number of people at risk of hunger due to climate change is about 80 million by 2080 under the model HadCM3 simulation scenario. Regionally, climate change effects were to further widen the gap between developed and developing countries, especially in tropical semi-arid developing countries (Fisher et al., 2005). The rural populations in semi-arid and arid zones are exposed to higher risk of malnutrition since they have fewer options to adopt (FAO, 2008). However, even if the mitigation measures were taken now, the effects would not be felt until 2050 due to lags in the climate system (Tubiello and Fischer, 2007). This makes an urgent call to actions of adaptation, which should be implemented as soon as possible to reduce the anticipated negative effects.

1.2.2. Land availability

Available agricultural lands refer to the arable lands which can be used for agricultural purposes. Arability mainly depends on soil properties, local climate, topography condition, and infrastructure availability like irrigation facilities (FAO, 1985). Its estimation can be further divided into two problems, firstly how many lands are suitable for agricultural purposes and secondly how suitable those lands are. The
availability, however, also relies on whether these suitable lands have been developed for other purposes. According to FAO’s report (2000), the global gross potential arable land (rainfed) is 4.14 billion hectares while the actual arable land is only 1.46 billion hectares at the end of last century. The arable lands that are not actually used for agriculture are mainly occupied by protected land (for nature, etc.), like forests, and human settlement (FAO, 2000).

Climate change is definitely going to have enormous impacts on agricultural land availability. Rising sea level may reduce the amount of land available for agriculture (IPCC, 2007). Temperature increase is likely to lengthen the growing season at higher latitudes, which can probably improve the land suitability in those regions. Shrinking arable land will jeopardize the food security (Liu, 2006). Although this work does not consider the land reduction caused by ocean expansion, reliable estimations of the rainfed arable land estimation can still be expected.

1.2.3. Crop yield

Climate change effects on crop yields are expected to vary differently from region to region across the globe. Yields in the developed world are likely to benefit whereas negative effects are expected in the developing world (excluding China) (Parry et al., 1999). Regions in the northern high latitudes and around mountains where low temperature used to be a constraining factor may expect an increase in yield attributed to rising temperatures (Muller et al., 2010), while in warmer, lower latitude regions, increased temperatures increase respiration, resulting in less than optimal conditions for net growth (Olesen and Bindi, 2002).

Besides temperature, yield is influenced by two other uncertain factors, CO₂ fertilization effects and water availability. Specifically, higher atmospheric concentrations of CO₂ improve crop yields by increasing water-use efficiency and the rate of photosynthesis of most crops (Darwin, 2001; Long et al., 2006). The direct effects of CO₂, however, will be small in regions where low fertilizer-use or other factors inhibit crop growth, such as the arid and semi-arid regions in Africa (Darwin, 2001). In addition, decreased soil moisture also attributes to crop yield reduction (Long et al., 2006; Cai et al., 2009). Hence, although higher CO₂ concentrations
generate beneficial effects on crop yields, it is unlikely to offset the other negative consequences due to climate change and global crop yields as a whole probably expect reduction (Parry et al., 2004; Long et al., 2006). Furthermore, changes in temperature and precipitation patterns due to global warming will likely alter the geographic distributions of pests and diseases, attributing to more uncertain effects on yield (Patterson et al., 1999).

Climate change is likely to increase the number of people at hunger risk through this century in terms of its impacts on crop yield compared to the reference scenario without climate change (Schmidhuber and Tubiello, 2007). The magnitudes of the influences depend on the level of economic development and CO₂ effects (Fischer et al., 2005; Parry et al., 2004). Furthermore, Sub-Sahara Africa is likely to become the most food-insecure region as a result of the socio-economic development paths assumed in SRES scenarios (Schmidhuber and Tubiello, 2007).

1.3. OUTLINE

The goal of this work is to estimate the impacts of climate change on global agricultural land availability, both quantitatively and qualitatively. The land availability assessment includes estimates of how many lands are available and how suitable these available lands are for agricultural purposes, that is, the land suitability for arable purposes. Climatic variables, topography and soil properties are adopted for the estimation. Spatially explicit global distribution maps of the arable lands will be achieved for both the historical period and the projected period, and then the changes of arable lands will be examined. seven important agricultural countries/regions are discussed in more detail to have a closer insight of the effects. In the end, discussions regarding issues of food security and the prospect of bioenergy will be presented based on the land availability results.

The rest of the dissertation is organized as follows:

Chapter 2 presents the methodologies used in this study. A thorough description of data preparation is given to provide more background knowledge. After that, the main input factors adopted in later simulation parts are introduced and explained in detail, and then the methods of processing climate data are illustrated. Definition and
classifications of land suitability are provided and a brief description of the fuzzy logic is given, which is used to estimate the land availability.

Chapter 3 presents the results of the land availability assessment. Detailed analysis, as well as tables and figures are provided. Climate changes are analyzed based on climate zones, land uses and other factors. The changes of the agricultural land distribution are explored and explanations about the underlying causes are given. Impacts on food security are also going to be examined.

Chapter 4 contains discussions and conclusion of the study. Discussions regarding the uncertainties involved in this study, limitations and future work possibilities are presented. Conclusions are going to be addressed in the end.
1.4. FIGURES

Figure 1.1 Global mean temperature departures from 1850-2010
(Source: Schlesinger & Ring, 2010)

Figure 1.2 Multi-model global averages of surface warming (relative to 1980-1999) for the SRES scenarios A2, A1B and B1 (Source: IPCC, 2007a)
CHAPTER 2
DATA AND METHODOLOGY

The data and methodology of this thesis follow the outputs of a research project supported by the Energy Bioscience Institute’s project (Cai et al., 2010), which I have participated in. A fuzzy logic approach was developed (see Appendix) for agricultural land suitability assessment, taking into account four input factors, which are soil properties, soil temperature regimes, soil moisture regimes and topography. Among them, soil temperature regimes and soil moisture regimes are influenced by climate changes. The method is modified in this thesis. To better represent the climatic impacts, Humidity index and air temperature are adopted to replace soil moisture regime and soil temperature regime respectively, which can reflect the changes more directly. This chapter contains the description of the climatic data processing and the modification of the fuzzy logic approach, including the challenges and difficulties involved. The four input factors and the land suitability assessment criteria are illustrated in detail.

2.1. DATA PREPARATION

The research work uses climatic, soil property, and topographic data to assess the agricultural land suitability, as summarized in Table 2.1. In particular, the uncertainty in climate change projection is handled in this thesis. The climate data coming from various sources involve numerous uncertainties due to observational errors and simulation model limitations. Meanwhile, their resolutions and extents are also different. All these present challenges for the data processing. Thus, the data preparation is an important task and it lays the ground for the research goal of this thesis.

2.1.1. Climate data

Climatic data used in this work contains items of two periods: historical climatic data, which consist of observational 30-year average monthly global land surface temperature and precipitation and simulated 30-year average monthly global temperature and precipitation for 1961-1990; and projected climatic data, that is, 30-year average global temperature and precipitation for 2070-2099. Observational
historical data are obtained from the database of Climatic Research Unit (CRU) at the University of East Anglia (New et al, 1999), while simulated data of thirteen General Circulation Models (GCMs) are provided by the GCM developers (IPCC, 2007).

Observational historical data are records of global land surface for twelve months. The resolution is 0.5 degree by 0.5 degree and the extent is about 60N-56S, 180W-180E. Nevertheless, to keep a consistent resolution with GCM simulated data in order to calculate the root mean square errors between GCM simulated climatic data and observed records for 1961-1990, the grids were aggregated to 2 degrees by 2 degrees. This is because ten of the thirteen GCMs provide their outputs with the coarse resolution.

The 13 GCMs selected for this study according to data availability and simulation requirement provide the largest number of samples for model variability analysis. The GCMs are CGCM3.1, GFDL-CM2.0, GFDL-CM2.1, GISS-AOM, FGOALS-g1.0, INM-CM3.0, IPSL-CM4, MIROC3.2 (hires), MIROC3.2 (medres), ECHAM5/MPI-OM, MRI-CGCM2.3.2, CCSM3, UKMO-HadCM3. These models provide projection during the period of 2070-2099 under two emission scenarios, A1B&B1. However, the resolutions of the 13 GCMs are different. The coarsest is model INM-CM3.0, with the resolution of 4° * 5° (latitude by longitude), and the finest is model MIROC3.2 (hires), with the resolution of 1.125° by 1.125°. The resolution difference poses difficulty for data processing. For the simplicity but without loss of significance, the simulated grid cells were resampled to 2° * 2° using ArcGIS.

Simulated temperature and precipitation data by GCMs have the extension from 90N to 90S, and 0-360, indicating that the data start from the longitude around England and then extend east. This hampers the following data processing, since the matrices of the historic data and simulated data are in different order, that is, the same entry refers to different locations in the two datasets. To keep consistent extents with observational climatic data and other input data, the GCM simulated data were reorganized so that the simulated data start from the longitude around Alaska and then extend east. However, since there is some data lost at the boundary during the process
of resampling, after the reorganization, there is a blank band with no data in the middle. Fortunately, the no-data band is not wide, so reliable and comprehensive global estimation can still be expected.

2.1.2. Soil property data

The soil property data used in this work are part of Harmonized World Soil Database (HWSD) by FAO/IIASA (FAO, 2009). The HWSD was developed for climate change impact assessment and for the FAO/IIASA Global Agro-ecological Assessment study. It contains sixteen soil properties for global land surface (shown in Table 2.2) with a resolution of 30 arc-second. The soil property ratings are assigned with a value between zero and one. For each of the five categories shown in Table 2.2, the category rating takes the average of the ratings of the properties belonging to the category. The overall soil productivity rating is the product of the ratings of all the categories. In the process of calculation, the soil ratings are scaled to integers by timing 1000. This high-resolution soil property database lays a reliable groundwork for future calculation.

2.1.3. Topography data

The topography data are Global Terrain Slope (GTS) data from Fischer et al. (2008). GTS was compiled using elevation data from the Shuttle Radar Topography Mission (SRTM) with 30 arc-second resolution. GTS includes eight slope classes: 0-0.5%, 0.5-2%, 2-5%, 5-10%, 10-15%, 15-30%, 30-45%, and >45%. The slope files contain 8 maps, in which the value of each pixel represents the area percentage belonging to this particular slope class. For a cell at one location, the sum of all 8 files is equal to 100. These files determine the final outputs’ formats, which are in area percentage as well.

2.1.4. Land-use data

The land-use data adopted in this study were obtained from the remote-sensed landcover database from International Geosphere-Biosphere Program (IGBP). The 1 km land cover map was obtained from the Advanced Very High Resolution Radiometer (AVHRR) for all terrestrial surfaces (ISLSCP, 2004). It consists of 16 classes of landcover: forest, shrubland, savanna, grassland, cropland, cropland/natural
vegetation mosaic, wetland, urban and built-up, snow and ice, barren or sparsely vegetated, and water bodies (Biradar et al., 2009). This high resolution land use database provides an excellent source to compare with the simulated results, as a reference for calibration.

2.2. PROCESSING CLIMATE CHANGE PROJECTIONS

According to the literature, the ensemble of GCM projections is more reliable than a single GCM (Murphy et al., 2004) for applying climate change projections to a particular region. Hence the possible largest sampling of GCMs simulations was collected in this study based on the data availability and the requirement of ensemble scenarios. GCM simulations involve considerable variations and uncertainties due to different climate sensitivity and forcings (Knutti et al., 2008; Collins et al., 2006; Forster and Taylor, 2006). Figure 2.1 displays the seasonal variations of the 13 GCMs’ projected temperatures, with the frequency representative of the GCM numbers within that range. It is seen that the ranges of the simulations are pretty large, varying from 4 Celsius in spring to 8 Celsius in winter.

The simple average method (SAM) and root mean square error minimization method (RMSEMM) are the two most widely used ensemble approaches. SAM assumes that there is no information available to support the model preference and adopts the honest way by assigning an equal weight to each model (de Fraiture, 2003), but it ignores the variations in quality between models (Murphy et al., 2004). RMSEMM determines the weights of simulation models according to their abilities to reproduce the historic records. However, observational data also involve error and uncertainty, and the reproducing abilities are not necessarily representative of the projection skills. Laurent and Cai (2007) identified an optimal tradeoff coefficient to combine SAM and RMSEMM for central United States. Nevertheless, this coefficient is regionally sensitive and varies with parameters, which makes it difficult, if not impossible, to implement globally. Therefore, to deal with the uncertainties involved in observational data and simulation models, the 13 GCMs are combined by both SAM and RMSEMM so that the possible range of all possibilities can be achieved.

2.2.1. Simple average method (SAM)
For the 13 GCMs, each has 12 projected monthly precipitation values and 12 projected monthly temperature values for the period of 2070-2099. SAM is to average the 13 GCMs’ projection of each month, assuming that each GCM is equally good for predicting. After the SAM combination, we have 12 monthly precipitation and 12 monthly temperature txt files in total for the 13 GCMs for each emission scenario.

2.2.2. Root mean square error minimization method (RMSEMM)

Under this method, the best combination of GCMs is targeted rather than the combination of the best GCMs (Laurent and Cai, 2007). Probabilities are assigned to each GCM so as to minimize the root mean square error between the 30-year average observational data and weighted simulations.

\[
W = \sum_{t=1}^{12} \sum_{i=1}^{13} p_i (G_{i,t} - O_t)^2
\]

For \(t=1, 2\ldots12, i=1, 2\ldots13 \) (2-1)

where \(O_t\) is the monthly observational record, \(G_{i,t}\) is the monthly simulation of one GCM, \(p_i\) represents the probability assigned to a single GCM, \(W\) is the annual root mean square error between the weighted simulation and the observation.

The optimization for each cell of each parameter (precipitation & temperature) was performed in GAMS, with a Fortran code calling it and looping through all grid cells globally. It should be noted that the probabilities of precipitation and temperature for an individual GCM are different. The probability is calculated separately for historical precipitation and temperature (1961-1990) by GAMS for each grid. After minimizing the root mean square error, an optimal set of probabilities \(\{p_i, i=1, 2\ldots13\}\) is achieved for each climate variable in every cell. Here, it is assumed that the probability sets which minimize the historical observation-simulation root mean square errors are also optimal for future period simulations. Next, 13 GCMs’ projections are multiplied by the sets of probabilities. In the end, we have 12 global monthly precipitation projections plus 12 global monthly temperature projections for each emission scenario.

2.3. LAND SUITABILITY ASSESSMENT UNDER CLIMATE CHANGE

In this study, the global arable land availability estimates consist of assessing how much land is suitable for agricultural development and how much of that is
available. Methodology is developed to access the land suitability and possible climate induced changes, followed by analysis regarding land availability. Fuzzy logic is adopted, which is a powerful tool to address data variability, imprecision and uncertainty (Joss et al., 2008).

This thesis contains a baseline estimate of suitable arable land for 1961-1990 and the assessments of future scenarios. Parameters and fuzzy rules are calibrated based on the results of baseline, and then applied in the future scenarios. It is assumed that parameters and rules which are able to simulate the current arable lands can also predict the potential agricultural lands in future climate conditions.

2.3.1. Land suitability

FAO proposed land evaluation in terms of two broad classes, “suitable” and “not suitable” based on climatic and terrain data and soil properties crop-wise (Ahamed et al., 2000). The suitable class is further divided into three categories: highly suitable, moderately suitable and marginally suitable (FAO, 1976). Correspondingly, in this study, the classification is simplified into three categories: suitable, marginally suitable and not suitable.

Suitable agricultural lands are lands having no significant, minor or moderately severe limitations for sustained applications to a given use. These lands should not have more than one severe limitation among the four factors for the estimation. In the real world, these lands should be mostly used as croplands. Marginally suitable lands are those lands with limitations that in the aggregate are severe for sustained application to a given use, but are still marginally economical (FAO, 1976). It is assumed that they should not have more than one severe and one moderate limitation or two moderate limitations. These lands are most likely to be in the current use as pasture land or mixed vegetation and cropland, but are also possibly used as cropland, which may be the case in some developing countries, left as fallow or forests. Furthermore, the marginally suitable lands can be potentially used for biofuel crops, like miscanthus and switchgrass (Tilman, 2009). The sum of suitable lands and marginally suitable lands are the potential arable lands.

Four factors are adopted in this study to estimate the land suitability, including
soil properties, slope, humidity index and air temperature. Soil properties and slope have been explained above, and the Humidity index and air temperature will be introduced in the following. These two factors are chosen because they can reflect the climate change impacts more directly than soil moisture regimes and soil temperature regimes.

Fuzzy logic is adopted to estimate the agricultural land suitability attributed to its capability of handling classification uncertainty and ambiguity (Singpurwalla and Booker, 2004). It provides a treatment of the ambiguity and uncertainty involved in generating realistic continuous classifications (Singpurwalla and Booker, 2004) and has been widely adopted to assess agricultural land suitability (Phillis & Andriantiatsaholiniaina, 2001; Sicat et al., 2005; Joss et al., 2008).

The fuzzy logic modeling process consists of three steps: fuzzification, fuzzy rule interference, and defuzzification. The first step is to assign the degree of class membership to each factor for each of three linguistic variables (Suitable, Marginally Suitable, and Not Suitable) through empirical membership functions (Joss et al., 2008). Next, fuzzy rules need to be determined which model the productivity of each piece of land into one of three categories: Suitable (H), Marginally Suitable (M) and Not Suitable (N). The rules consist of a condition part (IF-), and a conclusion part (THEN-) (Joss et al., 2008). For each category, one or several rules are combined to give one value. The determination of the rule combinations are through a learning process. Simulation results are compared with actual land-use data and modified to match the reality as close as possible. Suitable land rules are calibrated based on cropland and mixed cropland (IGBP), while marginally suitable land rules refer to pasture lands (FAOSTAT). The calibrations are accomplished regionally considering the spatial variability. Finally, defuzzification translates the fuzzy linguistic outputs into one crisp value (Oberthur et al., 2000). The overall suitability is usually accomplished through membership functions (Joss et al., 2008) and here the rule of “Center of Maximum” is used. Thresholds for each category are defined and the final outputs are the area percentage of each grid cell whose overall suitability is in excess of the classification thresholds for H, M and N, respectively. More details of the fuzzy
logic approach are presented in the appendix.

2.3.2. Humidity index

Humidity index (HI) is a numerical indicator of the degree of dryness at a given location. There are different means to define this concept. The ratio of average annual Precipitation (P) to Potential Evapotranspiration (PET) (UNEP, 1992) is taken as Humidity Index (HI) in this work due to the data availability. The land classification based on HI is shown in Table 2.3. We can see that small HI represents high Humidity, and land is classified as humid when the HI is greater than 0.65. The calculation procedures are listed as follows:

1) Prepare the projected global precipitation (average annual precipitation) and temperature (mean monthly temperature) text files
2) Prepare an input file to represent the number of days of each month (day no.txt)
3) Prepare an input file to represent the average day length of each month for each row(mean value of two latitudes)(a matrix of 90*12)

Sunrise and sunset hour angle (hour angle is defined as the longitude of the subsolar point relative to its position at noon, 15° per hour, morning has negative hour angle and afternoon has positive hour angle) $h_0$

$$\cosh h_0 = -\tan \phi \tan \delta$$  \hspace{1cm} (2-2)

Here $\Phi$ is the latitude. $\delta$ is the declination angle (the declination of the sun is the angle between the equator and a line drawn from the centre of the Earth to the centre of the sun), and it varies between +23.45° at northern summer solstice (June 21) to -23.45° at northern winter solstice (December 21).

Declination approximation equation (Cooper, 1969):

$$\delta = 23.45 \times \sin \left[\frac{360}{365} \times (284 + N)\right]$$ \hspace{1cm} (2-3)

where N is the day number, Jan 1st is day 1 and so on

Thus, the hours between the sunrise and sunset can be calculated as

$$L = \frac{2 \arccos h_0}{15°}$$ \hspace{1cm} (2-4)
The result of day length is shown in Figure 2.2

4) Calculate the heat index $I$

$$I = \sum_{i=1}^{12} \left( \frac{t}{5} \right)^{0.514} \tag{2-5}$$

where $t$ is the mean monthly temperature in Celsius

5) Calculate the exponent $\alpha$

$$\alpha = 0.000000675I^3 - 0.0000771I^2 + 0.01792I + 0.49239 \tag{2-6}$$

6) Calculate the potential evapotranspiration (PET)

$$PET = 16\frac{L}{12}\left( \frac{N}{30} \right)\left( \frac{10t}{I} \right)^\alpha \tag{2-7}$$

where $t$ is the mean monthly temperature in °C and PET is the monthly evapotranspiration in millimeters. Although there are several ways to calculate the PET, the one described above is chosen due to the data availability and calculation simplicity.

7) Calculate the Humidity Index (HI)

$$AI = \frac{P}{PET} \tag{2-8}$$

where $P$ is the average annual precipitation and $PET$ is the average annual potential evapotranspiration

The procedures listed above are performed for both the baseline and projected scenarios and five global Humidity Index grid maps are generated.

2.3.3. Soil temperature regime

Soil temperature regime is adopted to assess the temperature effect on land suitability. According to the global soil temperature regime developed by USDA-NRCS (1997), there are 14 soil temperature classes, namely, Ice, Hypergelic, Pergelic, Gelic, Cryic, Frigid, Mesic, Thermic, Hyperthermic, Megathermic, Isomesic, Isothermic, Isohyperthermic, and Isomegathermic. Soil temperature regime is related to air temperature. Statistical analysis will be performed to explore the relationship between these two factors.

The approximate air temperature range for each class is shown in Table 2.4. Although there are overlaps among these ranges, an increasing trend can be seen from
Figure 2.3. The lines represent the air temperature ranges of one regime, and the block on the line shows the mean value. Classes 3 and 4 correspond to air temperatures below 265 K; air temperature within classes 5-8 is mostly within the range of 265 K~280 K; the air temperature in classes 9-16 is higher than 280 K. The findings of these relationships are of great value when incorporating the air temperature increase into the future land suitability estimate.
### 2.4. TABLES AND FIGURES

**Table 2.1 Global Datasets adopted in this study**

<table>
<thead>
<tr>
<th>Databases</th>
<th>Resolution</th>
<th>Sources</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Soil</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Harmonized World Soil Database (HWSD)</td>
<td>30 arc-second</td>
<td>FAO/IIASA, 2009</td>
<td>The HWSD was developed for climate change impact assessment and for the FAO/IIASA Global Agro-ecological Assessment study. See Table S3 for sixteen soil properties.</td>
</tr>
<tr>
<td><strong>Topography</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global Terrain Slope (GTS)</td>
<td>30 arc-second</td>
<td>Fischer et al., 2008</td>
<td>GTS was compiled using elevation data from the Shuttle Radar Topography Mission (SRTM) with 3 arc-second resolution. GTS includes eight slope classes: 0-0.5%, 0.5-2%, 2-5%, 5-10%, 10-15%, 15-30%, 30-45%, and &gt;45%.</td>
</tr>
<tr>
<td><strong>Soil temperature regime (STR)</strong></td>
<td>2 arc-minute</td>
<td>NRCS 2001</td>
<td>STR uses sixteen indices (1-16): ocean, inland water body, ice, Hypergelic, Pergelic, Gelic, Cryic, Mesic, Thermic, Isomesic, Hyperthermic, Megathermic, Isomegathermic, Isothermic, and Isohyperthermic.</td>
</tr>
<tr>
<td><strong>Historic Temperature</strong></td>
<td>0.5 arc-degree</td>
<td>New et al., 1999</td>
<td>Mean monthly temperature during 1961-1990</td>
</tr>
<tr>
<td><strong>Simulated Temperature</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>International Panel on Climate Change</td>
<td>Different resolutions</td>
<td>IPCC, 2007</td>
<td>GCM simulated monthly temperature for historic period 1961-1990 and projected period 2070-2099</td>
</tr>
<tr>
<td><strong>Historic Precipitation</strong></td>
<td>0.5 arc-degree</td>
<td>New et al., 1999</td>
<td>Mean monthly precipitation during 1961-1990</td>
</tr>
<tr>
<td><strong>Simulated Precipitation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>International Panel on Climate Change</td>
<td>Different resolutions</td>
<td>IPCC, 2007</td>
<td>GCM simulated monthly temperature for historic period 1961-1990 and projected period 2070-2099</td>
</tr>
<tr>
<td><strong>Land cover</strong></td>
<td>30 arc-second</td>
<td>Biradar et al., 2009</td>
<td>IGBP includes the various land cover types: forest, shrubland, savanna, grassland, cropland, cropland/natural vegetation mosaic, wetland, urban and built-up, snow and ice, barren or sparsely vegetated, and water bodies</td>
</tr>
</tbody>
</table>
Table 2.2 Soil Properties from HWSD

<table>
<thead>
<tr>
<th>Category</th>
<th>Index</th>
<th>Soil Property</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topsoil</td>
<td>1</td>
<td>Soil organic matter</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Bulk density</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Clay content</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>pH</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>Sodium adsorption ratio</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>Carbonates</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Gypsum</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>Cation-exchange capacity</td>
</tr>
<tr>
<td>Soil profile</td>
<td>10</td>
<td>Depth to restrictive layer</td>
</tr>
<tr>
<td></td>
<td>11</td>
<td>Available water capacity in the root zone</td>
</tr>
<tr>
<td>Subsoil water features</td>
<td>12</td>
<td>Permeability</td>
</tr>
<tr>
<td>Subsoil toxicity</td>
<td>13</td>
<td>Sodium adsorption ratio</td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>Electric conductivity</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>Cation-exchange capacity</td>
</tr>
<tr>
<td>Subsoil reaction</td>
<td>16</td>
<td>pH</td>
</tr>
</tbody>
</table>

Table 2.3 Classifications of Humidity Index and corresponding area percentage

(Source: UNEP, 1992)

<table>
<thead>
<tr>
<th>Classification</th>
<th>Humidity Index</th>
<th>Global land area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hyperarid</td>
<td>HI &lt; 0.05</td>
<td>7.5%</td>
</tr>
<tr>
<td>Arid</td>
<td>0.05 &lt; HI &lt; 0.20</td>
<td>12.1%</td>
</tr>
<tr>
<td>Semi-arid</td>
<td>0.20 &lt; HI &lt; 0.50</td>
<td>17.7%</td>
</tr>
<tr>
<td>Dry sub-humid</td>
<td>0.50 &lt; HI &lt; 0.65</td>
<td>9.9%</td>
</tr>
<tr>
<td>Humid</td>
<td>HI &gt; 0.65</td>
<td>39.2%</td>
</tr>
</tbody>
</table>

Table 2.4 Air temperature ranges for soil temperature regimes

<table>
<thead>
<tr>
<th>Regime</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower bound</td>
<td>245</td>
<td>255</td>
<td>265</td>
<td>270</td>
<td>270</td>
<td>276</td>
<td>278</td>
<td>287</td>
<td>292</td>
<td>299</td>
<td>290</td>
<td>292</td>
<td>296</td>
<td>299</td>
</tr>
<tr>
<td>Upper bound</td>
<td>255</td>
<td>265</td>
<td>272.5</td>
<td>272</td>
<td>280</td>
<td>280</td>
<td>287</td>
<td>292</td>
<td>300</td>
<td>302</td>
<td>298</td>
<td>296</td>
<td>300</td>
<td>302</td>
</tr>
</tbody>
</table>
Figure 2.1 Seasonal statistics of 13 GCM projections for 207-2099

(Source: D. Lindner, 2010)

Figure 2.2 Annual day Lengths for different latitudes
Figure 2.3 Air temperature correlations with soil temperature regime
CHAPTER 3
RESULTS AND DISCUSSIONS

This chapter presents results and discussions on global climate change projections and their impact on agricultural land, especially the underlying trends of the climatic factors and possible impacts on land suitability. Agricultural land suitability outcomes under both historic and projected scenarios will be provided. Exploratory insights are provided for the whole world and seven important agricultural regions for more detailed information. Moreover, climate change associations with other geographic variables, such as the impacts of altering arable land availability on food security and biofuel prospects in terms of land availability are discussed in the end.

3.1. CLIMATIC INDICATOR CHANGES

Before assessing the land suitability, climatic factors are examined for both 1961-1990 and 2070-2099 periods. Changes of air temperature, precipitation and Humidity Index (HI) are explored and analyzed to obtain insights into their impacts on land suitability evaluation.

3.1.1. Air temperature changes

Firstly, temperature alteration trends of the whole world for each month are examined by averaging the monthly temperature of the entire globe. Figure 3.1 shows the monthly global land mean temperatures under five scenarios, including two emission scenarios combined with two ensemble approaches and the historic observations, namely, A1B-SAM, A1B-RMSEMM, B1-SAM, B1-RMSEMM, and CRU. It can be seen from Figure 3.1 that global mean temperatures projected in A1B are higher than those of B1, and RMSEMM generates values greater than SAM. All four future scenarios present higher temperatures than the 1961-1990 baseline, which displays the global warming trend.

Secondly, the annual average global patterns of five scenarios are presented in Figure 3.2- Figure 3.5, showing the spatial distribution of the changes. Globally, the annual average temperature changes under A1B emission scenario are greater than
those under B1 scenario. The change ranges for A1B through SAM and RMSEMM are [-5.7, 11], [-6.2, 12.3] in Celsius, respectively, and [-7.2, 10.6], [-6.8, 11.9] in Celsius under B1. Using the same ensemble approach, A1B results in higher maximum increase and lower decrease than B1; while under the same emission scenarios, RMSEMM generates higher maximum increase than SAM.

Regionally, under the A1B emission scenario, high latitudes of North America and east Russia may expect the largest temperature increase of more than 5 Celsius, which can lengthen the growing season and may lead to expansion of the arable land. Most of other parts of the world are likely to have moderate increases of 1-5 Celsius. Temperature decreases may occur in west China, north India, Nepal, north Pakistan and west of Greenland. Under B1 scenario, the increases are milder than A1B. The Highest increases in north Canada are most likely within 5-7 Celsius. In the United States, increases in the east are larger than the west; while in South America, Chile is likely to have more severe temperature rising than Brazil. Africa, India, Australia, and west Europe have relatively high confidence to experience moderate warming, while the changing trends in China and east Europe are subject to much uncertainty. The projections in these two regions do not show clear patterns of the alteration ranges. A1B-SAM, A1B-RMSEMM and B1-RMSEMM show moderate increases of 1-5 Celsius in east China and east Europe, but B1-SAM predicts only slight warming of 0-1 Celsius along with some regions with decreases in temperature. If the majority of the projections are assumed correct, these two places may expect moderate warming, but cautions should be taken regarding the uncertainty and variability within the projections.

3.1.2. Precipitation changes

Globally averaged monthly precipitations for five scenarios are presented in Figure 3.6. It is shown that data generated by RMSEMM display closer patterns to the historic data than SAM. Precipitations under A1B scenario are greater than B1 under the same ensemble approach. In addition, compared to CRU data, projected precipitations are greater from September to next June, while precipitations in July and August are smaller than in 1961-1990. This difference is more evident for SAM.
ensembles. In summary, with the same combination approach, global mean
temperatures and precipitations under A1B scenarios are greater than B1. Moreover,
under the same emission scenario, SAM generates more evenly distributed
precipitations and lower temperatures than RMSEMM, which means that RMSEMM
scenarios probably expect more extreme events.

Precipitation changes by the same ensemble approach have similar patterns. Here
the A1B-SAM and B1-RMSEMM scenarios are taken as examples for analysis, as
shown in Figure 3.7 and Figure 3.8. Under both scenarios, the wide-spread high
latitude regions in the north hemisphere are likely to have 0-2 mm/day increase of
precipitation in both North America and Eurasia continents, which is likely to benefit
the agriculture lands. By contrast, southwest of the U.S., western South America,
exterior regions of Australia, and south Europe expect different levels of reduction in
precipitation, which will probably aggravate the aridity in some of those regions.
Some regions are subject to unclear changes where the scenarios do not achieve
agreement in projection, like northern Africa and India. This indicates these regions
are relatively more sensitive to the development paths, the climate sensitivity
assumptions, ensemble method and so on. The changes in those regions have a higher
probability than others to switch under different conditions.

3.1.3. Humidity Index changes

The calculated average AI for the period of 1961-1990 is shown in Figure 3.9.
The global AI map agrees with the common knowledge well. In this figure, redness
represents aridity, the redder the region, the drier it is. As shown on the map, Saharan
Africa, Middle East, interior Australia, western China and western America are arid.
The light red north of Canada area has values ranging from 0.25 to 0.5, which are
semi-arid according to the classification (UNEP, 1992). On a global soil moisture
regime map (USDA-NRCS, 1997), this region is permafrost. The reason for the low
AI may be due to the low precipitation. By contrast, the high AI in Greenland is
mainly due to the low PET resulting from the low temperature there. Similar
procedures are performed for the 4 projected scenarios.

The simulated 1961-1990 global AI map is compared with the map by Trabucco
and Zomer (2009). As can be seen from Figure 3.9 and 3.10, although the data periods and approaches to calculate PET are different, the global patterns of the Humidity Index agree with each other. The reason why the maximum value in Greenland in their map is 10 times larger than the simulation of this study is because the mean temperature in this region is so small that the AI is approaching infinity; to avoid deficit, a relatively larger value is assumed in the region possibly larger than what Trabucco and Zomer (2009) used in their study, causing the AI values to decrease in this region. Nevertheless, the assumption does not influence the values in other places and the global pattern. Moreover, the inconsistent resolution may also account for some differences. This study uses data with 2-degree resolution, while their work is around 1 km. The overall agreement verifies the reasonability of the AI method adopted in this thesis and indicates that this can be further used to reflect the climate change impacts.

As shown from the Humidity Index maps of the projected scenarios (Figure 3.11 – Figure 3.14), the global patterns are similar to the historical ones, but with some regional alterations. Sahara-Africa, interior Australia and mid-East remain the most arid regions, while South America gets drier than before. Thus, these regions expect less suitable lands for agricultural purposes due to the rising temperature and/or drier climate.

From both the AI change maps under A1B-SAM (Figure 3.15) and B1-RMSEMM (Figure 3.16), more precise understanding can be obtained. It is shown that Humidity Index is likely to decrease in most regions around the equator, including the east part of South America, mid-East, southeast America, Australia, India, Southeast Asia and southern China. In particular, Brazil, Columbia, Venezuela and Greenland are projected to experience the largest increase of AI, which means the climate in these regions would become drier than current conditions. Wetter climate is expected in northern Eurasia, Peru, Chile, and regions west of America and Canada.

3.2. LAND SUITABILITY ASSESSMENT

This part presents the simulation results of the agricultural land suitability for 1961-1990 period and four projected future scenarios. Maps and tables are explored
and illustrated at both global and regional scales. Interesting and important messages are pointed out and analyzed.

3.2.1. Baseline

In the EBI project’s framework (Cai, et al., 2010), soil property, slope, soil moisture regime (SMR) and soil temperature regime (STR) were adopted to assess the land suitability. However, in order to reflect the climate changes more directly, Humidity Index and air temperature are used to replace the SMR and STR. The fuzzy logic is applied to estimate the land suitability through three steps: fuzzification, rule interference and defuzzification (Joss et al., 2008). Membership functions are needed to process the fuzzification and they are illustrated in more detail in the following paragraphs.

The membership functions defined for Humidity Index in the fuzzy logic estimate are shown in Figure 3.17. The divisions are based on the classification of the aridity as shown in Table 2.3. Hyper-arid and arid lands are not suitable to plant crops, humid lands can provide sufficient water for agricultural purposes, while semi-arid and dry semi-humid lands are suitable for arability to some degrees. As displayed on Figure 3.9, Greenland is the most humid region, but it is constrained by temperature in the estimate.

The membership functions of soil temperature regimes are shown in Figure 3.18, with class 3, 5 and 9 as turning points. Based on the correlations between air temperature and soil temperature regimes, the membership functions are modified, with corresponding ranges of air temperatures representative of the other factor (Figure 3.19). Hence, air temperature records can be used in the fuzzy logic on behalf of the soil temperature and reflect the climate change impacts more directly.

After defining the membership functions and determining the fuzzy rules through calibration, the land suitability is simulated. The global suitable agricultural land and marginally suitable arable land maps for 1961-1990 are displayed in Figure 3.20 and Figure 3.21. Values of each pixel represent the area percentage in each cell belonging to a suitable or marginally suitable category. Redness indicates that 100% of the area of the grid is in the category, while blue means this cell does not belong. Suitable
agricultural land is defined by a threshold of 0.7 in the overall rating after fuzzy
calculation, and the threshold for marginally suitable land is 0.55.

Table 3.1 is the regional statistics of the suitable arable land and marginally
suitable land. The global potential arable land is 49.739 million km$^2$, with 19.69
million suitable lands and 30 million marginally suitable lands. Africa and South
America account for over 40% of the overall arable lands, 24% and 19.8%
respectively. By contrast, the conventional agricultural regions, like China, India and
Europe, only occupy 21.8% of the potential cultivable lands. Therefore, it seems that
there is great development space for agriculture in Africa and South America, which
have large arable areas that are not even half developed.

The potential arable lands calculated based on the natural factors are gross
potential arable land without taking the reality into consideration. Adjustments should
be taken to allow human settlement, like industry & residential use, and protected
land conservation (FAO, 2000). Protected land was defined by the IUCN World
Commission on Protected Areas (IUCN, 1994) as “An area of land and/or sea
especially dedicated to the protection and maintenance of biological diversity, and of
natural and associated cultural resources, and managed through legal or other
effective means.” This consists of important forests, woodlands, savannas, grasslands,
mountains, lake systems and deserts (Chape et al., 2003) and the area increases
continually from the middle of the last century. Settlement area is assumed to be
related with population (Alexandratos, 1995). In the reference scenario, the settlement
is calculated using 0.033 ha/person times the population; while in the projected
scenarios, the ratio is 0.03 ha/person considering the higher population density. The
population data used in the reference scenario is of 1992 due to the data availability. It
was assumed that 50% of the protected areas and 100% of the settlement lands
occupied the potential arable lands (FAO, 2000).

As shown in Table 3.2, the global gross potential arable land is 49.739 million
km$^2$ and the net available land after substracting the protected lands & settlement is
41.321 million km$^2$. From the ratios of actual cropland to net available land row, it is
seen that Africa and South America’s current cropland occupy a small portion (less
than 20%) of the total arable land, while India and Russia used more than 60% of the potential arable land. Thus, it seems that the greatest potential for agricultural expansion lies in Africa and South America, which has been indicated in FAO’s land resources report (2000). However, one issue worth noticing is that rain forests in Africa and South America that are not included in the protected land category may occupy a large portion of the potential for further agricultural development. Rain forests, in particular, are of vital meanings to human society, both biologically and economically (FAO, 2000). Cautious plans and decisions should be undertaken for agricultural expansion in these two regions (FAO, 2000; Ramankutty et al., 2002).

3.2.2. Future Scenarios

The determined membership functions and calibrated fuzzy rules are implemented in the projected scenarios, assuming those from historic simulations are applicable to the future scenarios as well. Soil property and slope data remain the same, while the climatic data are adopted from the IPCC projected AR4 series (2007) with the assessment discussed in section 3.1. The simulated suitable & marginally suitable land outcomes are presented in Table 3.3 and Figure 3.22-3.29.

As seen from Table 3.3, the global potential arable lands decrease under A1B emission scenario and increase for B1. Under the same emission scenario, SAM generates more optimistic results than RMSEMM, with greater increasing and smaller decreasing magnitudes. China, Russia and United States whose potential arable lands may increase 22.63%-35.7%, 36.83%-67.06%, and 3.66%-16.89% respectively, are most likely to benefit under the changing climate. The increases mainly attribute to the rising temperature and wetter climate at the north high latitudes, as further illustrated in the following. By contrast, Africa, Europe, South America and India expect different levels of reduction in potential arable lands, which are mostly due to the over-optimal temperature and/or decreasing Humidity Index in at least some parts of these regions. Africa suffers the greatest loss in scenario A1B-RMSEMM, by 18.09%, while South America loses 20% in A1B-SAM. The alteration for Europe and India are comparatively stable, with reductions ranging from 10.88% to 17.19% in Europe and 1.73% - 3.6% in India. A clear pattern can also be achieved from Figure
3.30. It can be seen from it that China, Russia and U.S. can anticipate increases in potential arable lands while Africa, India, Europe and Russia may experience reductions. The regional alteration trends stay consistent under all four scenarios, but with various magnitudes. This verifies the reliability of this work.

The suitable and marginally suitable lands in most regions have consistent alteration trends as the potential arable land, so we cannot tell whether a switch occurs between the suitable and marginally suitable land. However, both the potential arable land and suitable land reduce in India while the marginally suitable land increases, suggesting that some suitable land switches to marginally suitable land in the future.

Comparing the regional results under A1B and B1 emission scenarios, most regions show greater increase and larger decrease under A1B than B1 except United States. That is, with the same ensemble approach, Russia and China expect higher increase under A1B, while Africa, South America, India and Europe may have more serious reductions. This may attribute to the higher temperature rising of the A1B scenario. The reason why U.S. presents greater growth under B1 probably is due to water constraint.

Compared to the study by Ramankutty et al. (2002) which assumed a CO₂ concentration of 710 ppmv for the 2070-2099 period, the regional alteration trends agree while the global numbers differ. In this work, A1B assumes CO₂ equivalent GHG concentrations at 850 ppmv by 2100 and B1 assumes 600 ppmv (IPCC, 2007). Global potential arable land is projected to reduce by around 0.5-0.8 million km² under A1B scenarios and increase by around 1-2 million km² under B1 scenarios, while Ramankutty et al. (2002) predicted an increase of 6.6 million km² globally. Regions at the high latitudes of the north hemisphere are projected to expect more arable land by both studies, yet with different magnitudes. Arable land in Russia is simulated to grow by around 1.1 million km² here while they predicted another 3.4 million km² for former Soviet Union. The work projects an increase of around 1.2 million km² in China but Ramankutty et al. (2002) simulated 0.9 for China, Mongolia & North Korea. Both studies project reduction in land suitability at tropical regions, like Africa, South America and Oceania (Ramankutty et al., 2002).
Take China as an example to explore the reasons of the increased suitability. As shown in Figure 3.31 and 3.32, the merging of new suitable and marginally suitable land is in the mid- and west north China along the Great Wall. Originally, these regions are cold and dry. However, as projected by the GCM simulations, Humidity Index is likely to increase and the temperature may also expect moderate rises, which are presented in Figure 3.33 and 3.34. These two factors contribute to the growth of arable land in China.

Similar analysis is performed for Russia, Africa and South America. Russia may have an emergence of arable land in its west part, where both Humidity Index and temperature increase moderately (Figure 3.35-3.38). Suitable land increases slightly in the middle of Africa (Figure 3.39), which is most likely transformed from marginally suitable land (Figure 3.40); other parts of Africa may have a reduction of suitable agricultural land, which is associated with decreased Humidity Index and rising temperatures (Figure 3.41-Figure 3.42). This is because even moderate temperature rises in tropical regions can cause less-than-optimal condition for crops, and reduce the area of cultivable lands (Olesen and Bindi, 2002). In South America, the reduction of potential arable land occurs mainly in the Amazon region (Figure 3.43 & Figure 3.44), due to rising temperature and declining lower humidity index (Figure 3.45 & Figure 3.46).

Table 3.4 is the net available land calculation for the whole globe and seven regions. The 2050 population is adopted for future scenarios because it is projected as the peak value in A1B and B1 emission scenarios (Furuya et al., 2009). Although the projected global gross arable lands have minor reductions under A1B emission scenarios and improve slightly under B1, the net potential available lands for agriculture decrease in all future scenarios. The reasons attribute to the ever-growing population, climate change impacts, and additional protected area. For different regions, different reasons predominates. In Africa and South America, the net available lands decrease because of the climate change impacts and growing protected lands. China and Russia are likely to benefit from the climatic alterations, where impacts are large enough to offset the negative influences from rising population and
protected area. Europe may expect a reduction in net arable land resulting from the climate impacts, whereas India expects decreases due to climate change impacts and rapidly rising population. The United States may possibly experience a slight increase, with most of the benefit from climate counteracted by population growth.

The potentials for future agriculture expansion decrease globally for most regions except Russia, China and the United States. Russia and China are likely to receive increases in net potential arable since the climate changes benefit their land suitability for agriculture, while the current cropland of U.S. is smaller than that of 1992, leaving more space for further development. Despite the negative impacts of climate change, the regions with greatest agricultural development potential are still Africa and South America.

3.2.3. Irrigation

Irrigation is partially considered in the land suitability assessment. Irrigation includes full and supplementary irrigation. The former is applied to arid land with a very small amount of rainfall during the crop growth period and a Humidity Index close to zero. This part of irrigated land may not be included in the potential land availability by the method described above because it assumes a certain amount of rainfall is available for crop growth (i.e., the HI has a lower bound). The land with supplementary irrigation may be taken into account since the HI can be higher than the lower bound.

Nevertheless, to incorporate the irrigation factor more explicitly, a global irrigation map (Siebert et al., 2007) is adopted to estimate irrigated land. The value of each pixel on the irrigation map represents the irrigated area percentage. It is assumed that irrigation is implemented on marginally suitable land only, which means that irrigation makes the original marginally suitable land switch to suitable land for agriculture. Moreover, it is assumed that irrigation land will remain the same for the future and the current map is used for the projected scenarios. Table 3.5 shows the estimates for both baseline and projected scenarios after considering irrigation. Globally, potential arable land increases by around 1 million km\(^2\) compared to the early assessment. However it should be noted that this value does not represent the
total global irrigated area since some irrigated land is already accounted by the fuzzy
logic method as mentioned above.

3.3. DISCUSSIONS

3.3.1. Land assessment comparison

The simulated arable land outcomes are compared with the literature for verification. As mentioned in the methodology, during calibration, suitable lands were compared with actual croplands and marginally suitable lands were referred to the pasture lands. However, due to the large scales and coarse resolution of climatic data, exact matches are difficult to achieve. Besides, the current land uses can not wholly represent the potential arability. Thus, a lot of trials were performed to obtain as close as possible calibrations region by region, under the constraints of the defined categories.

Various studies are referred to in this study, as listed in Table 3.6. Nevertheless, the concepts adopted in these studies do not stay consistent and the statistical domains are not the same, which posts difficulty for comparison. Furthermore, the numbers from different researches vary a lot. Therefore I have tried to retain reasonable ranges of the simulated outcomes, instead of matching accurately.

The data that are used as criteria for justification can be divided into two categories. One is real landcover data, based on observations or surveys, and the other is simulated potential arable land. FAO-STAT (2009) and Ramankutty et al. (2008) provide the current agricultural land data. In FAO-STAT, “arable land” refers to the land under temporary agricultural crops and “agricultural area” has the similar contents of “arable land” in this and other studies. “Permanent meadows and pastures” are used to compare with “pasture land” in other studies as well as the marginally suitable land simulated by this work. FAO’s land resource report (2000) and Ramankutty et al. (2008) estimate the global potential arable land under historic climate conditions are compared with the results provided in this thesis.

Compared to the real land use data according to FAOSTAT (www.faostat.org), the estimated global potential arable land is slightly larger. Regionally, South America is assessed with much higher value of potential arable land than the sum of cropland
& pasture land in reality, indicating high potential for agricultural development. In other regions, estimates of potential arable lands by this work are greater than the literature, but still comparable. The reason for the higher assessments may be that many agriculturally suitable places are currently occupied by other uses, like forests, human settlements and so on. The estimated net potential arable lands are more comparable with the real data, which are even smaller than the currently occupied agricultural area (cropland + pasture land), indicating that some regions are using some not suitable land for agriculture.

In contrast with the simulated potential arable lands of FAO (2000) and Ramankutty et al. (2002), the global value from this work is greater by about 20%. The regional values simulated by this work are close to the larger number of the previous two studies. In previous studies, potential arable land is estimated as 32.91 million km$^2$ by Xiao et al. (1997) and 41.53 million km$^2$ by Cramer & Soloman (1993). However, FAO (2000) and Xiao et al. (1997) adopted 1931-1960 climatic data (Leemans & Cramer, 1991), which are colder than 1961-1990 globally (Hadley CRUT). On the other hand, Cramer & Soloman (1991) did not consider the topography constraint in their estimate. Ramankutty et al. (2002) adopted 1961-1990 climatic records, and growing degree days (GDD) to present the temperature constraint. Nevertheless, GDD vary with crops and the chosen base temperature of 5 Celsius is appropriate only for wheat, barley, rye, oats, flaxseed, lettuce, and asparagus (Wikipedia, 2010), excluding the possibilities suitable for other crops.

3.3.2. Climate changes and geographic variables

More detailed exploration is undertaken to examine the changes of climatic factors. The following maps display the temperature, precipitation and AI changes on current cropland and mixed vegetation & cropland (IGBP, 2000). A1B-SAM and B1-RMSEMM are selected as representative of the other scenario under the same ensemble approach, since the two scenarios under the same emission situation have similar patterns.

Most current croplands and mixed croplands expect temperature increase during the period 2070-2099 compared to 1961-1990, shown in Figure 3.47 and Figure 3.48.
Mideast U.S. is likely to have 4-5 Celsius higher temperature in scenario A1B-SAM), and the range is 3-5 Celsius in scenario B1-RMSEMM. The East coast of South America and India may experience a minor rising of 1-3 Celsius, and temperatures on European cropland are probable to increase 2-4 Celsius in the same period under both scenarios. The alteration range in sub-Sahara Africa is comparatively wide, ranging from 1 to 4 Celsius. Although the rising magnitude is not significant, it may decrease the crop yield in this region since the rises may cause the temperature to go beyond the optimal condition for crops. East China is likely to have temperature increase 1-3 Celsius under A1B-SAM scenario, and 2-4 Celsius for B1-RMSEMM. In summary, the croplands and mixed croplands may experience slight to moderate increases in temperature, regionally varied. In addition, the rises of temperature have different impacts at different locations. High latitudes where temperature used to be a constraint factor are likely to benefit from the change, while tropical and subtropical regions may bear the negative impacts.

Precipitation changes on cropland & mixed cropland are displayed in Figure 3.49 and 3.50. Precipitation in central U.S. and Canada croplands is projected to increase slightly, while it is possible to decrease in southeast U.S., Europe and eastern China are also likely to experience more rainfall in both scenarios, whereas decreases can be expected in southern regions of exterior Australia. However, disagreement of projections occurs in India and sub-Sahara Africa. In India, A1B-SAM predicts reduction in precipitin and B1-RMSEMM predicts minor increase. In sub-Sahara Africa, nevertheless, it is the opposite case. The inconsistency in those two regions indicates their sensitivity to emission scenario and ensemble approach.

The global Humidity index changes at croplands and mixed croplands are shown in Figure 3.51 and Figure 3.52, for two scenarios respectively. It can be seen that north high latitude regions in Canada, Europe and China expect slight increase of AI, which means these regions are getting more humid than the 1961-1990 period in the future. On the other hand, southern U.S., southern Europe, India, southern China, South America and Sub-Sahara Africa are likely to have more arid climate, with AI reduced in the two projected scenarios.
Koppen climate zone classification (Rubel and Kottek, 2010), which is one of the most widely used climate classification systems, is adopted to examine climate change by climate zone. It divides the global climate into five main categories, with subgroups classified mainly based on temperature and precipitation. According to the temperature changes aggregated by climate zones (Peel et al., 2007) (Figure 3.53 & Figure 3.54), the polar tundra regions at high latitudes of the north hemisphere are likely to experience the greatest temperature increases, while the equatorial winter day zones in Asia and most of equatorial monsoonal regions expect minor rises. The equatorial fully humid, monsoonal and winter dry zones in South America and cold arid desert region in Asia are projected with different magnitudes of changes, indicating the sensitivities and uncertainties in those regions. Other zones may have moderate increases in temperature, ranging from 2 Celsius to 4.

Precipitation changes aggregated by climate zones are displayed in Figure 3.55 and Figure 3.56. The equatorial fully humid and monsoonal zones in South America have high possibility to experience moderate reductions in precipitation. In addition, the warm temperate-fully humid-hot summer zones in U.S., China, and South America expect minor rainfall decreases. Polar frost in Greenland, hot arid desert in Australia and equatorial monsoonal & winter day zones in South Asia are subject to uncertainty. Most other regions in North America, northern Eurasia, and Africa will possibly receive slightly more precipitation. One issue worth noticing is that the precipitation in the snow-winter dry-extremely continental zone in Asia is predicted to increase significantly with high confidence.

Humidity Indexes are also aggregated by climate zones, as shown in Figure 3.57 and 3.58. Equatorial fully humid, monsoonal, and winter dry zones, warm temperate-fully humid-hot summer zones, hot arid desert zones, and hot arid steppe zones around the globe are inclined to experience reductions in Humidity Index, indicating those regions probably expect drier climate than the last century. By contrast, many snow climate zones in the north hemisphere are predicted with growing AI, which means these places might have more humid climate. Uncertainties occur in the polar frost zone, polar tundra zone and cold arid desert zones.
It seems that among the three climatic parameters, temperature, precipitation and Humidity Index, only AI displays a relatively clear pattern of association with the climate zones. The alteration patterns of temperature and precipitation are more relevant with the locations.

3.3.3. Biofuel prospect regarding land availability

Biofuels - fuels derived from plant materials - are sustainable new energy providers compared to traditional fossil fuels (The Royal Society, 2008). According to Tilman et al. (2006) and Searchinger et al. (2008), biofuel plants are recommended to use carbon-poor lands, such as abandoned or degraded agricultural lands, to avoid the additional greenhouse gas emissions from landcover converting. Thus, in this work, the marginally suitable lands that are currently mixed vegetation and cropland are assumed to be the suitable carbon-poor lands for biomass. Global and regional land estimates were implemented for both historic and projected scenarios, as listed in Table 3.7.

In the baseline scenario, the global suitable land for biofuel crops is 436 million ha, which is comparable to the previous global estimates of degraded or abandoned agricultural land, with 500 million ha from Tilman et al. (2006) and 386 million ha from Field et al. (2008). The region with the greatest potential is South Africa, followed by Africa. Under projected scenarios, however, the suitable lands decrease resulting from the climate changes. The magnitudes of reduction vary with the development paths, with A1B causing greater losses and B1 less. Yet, it is unclear how the expansion of the biofuel industry would affect the climate in the future. Hopefully it can contribute positively by reducing greenhouse gas emissions.
### 3.4. TABLES AND FIGURES

#### Table 3.1 Suitable agricultural land estimated for 1961-1990 (Unit: million km²)

<table>
<thead>
<tr>
<th></th>
<th>Africa</th>
<th>China</th>
<th>Europe</th>
<th>India</th>
<th>Russia</th>
<th>South America</th>
<th>U.S.</th>
<th>Global</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suitable arable land</td>
<td>5.258</td>
<td>1.885</td>
<td>2.219</td>
<td>1.177</td>
<td>0.235</td>
<td>2.793</td>
<td>2.037</td>
<td>19.693</td>
</tr>
<tr>
<td>Marginally suitable land</td>
<td>6.854</td>
<td>2.698</td>
<td>1.346</td>
<td>1.543</td>
<td>2.081</td>
<td>7.045</td>
<td>2.333</td>
<td>30.046</td>
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#### Table 3.2 Comparison of actual and potential arable land for rainfed agriculture of reference scenario (Unit: million km²)

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<th>Global</th>
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</thead>
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<td>0.6</td>
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<td>1.84</td>
<td>2.08</td>
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<td>0.39</td>
<td>0.15</td>
<td>0.30</td>
<td>0.05</td>
<td>0.10</td>
<td>0.09</td>
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<td>Actual cropland(1992)</td>
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<td>1.32</td>
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<td>1.69</td>
<td>1.34</td>
<td>1.12</td>
<td>1.86</td>
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<td>35.115</td>
<td>41.111</td>
<td>72.578</td>
<td>68.475</td>
<td>12.703</td>
<td>57.339</td>
<td>36.906</td>
</tr>
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</table>

**Sources and Notes**

Table 3.3 Suitable agricultural land simulated for projected 2070-2099 scenarios
(Unit: million km$^2$)

<table>
<thead>
<tr>
<th></th>
<th>A1B-SAM</th>
<th>A1B-RMSEMM</th>
<th>B1-SAM</th>
<th>B1-RMSEMM</th>
</tr>
</thead>
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<td>India</td>
<td>Europe</td>
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<td>2.711</td>
<td>0.988</td>
<td>1.687</td>
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<td>Marginally suitable land</td>
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A1B-SAM

<table>
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<th>A1B-RMSEMM</th>
<th>B1-SAM</th>
<th>B1-RMSEMM</th>
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<td>China</td>
<td>India</td>
<td>Europe</td>
</tr>
<tr>
<td>Suitable land for Agriculture</td>
<td>3.673</td>
<td>2.574</td>
<td>1.08</td>
<td>1.687</td>
</tr>
<tr>
<td>Marginally suitable land</td>
<td>6.248</td>
<td>3.133</td>
<td>1.557</td>
<td>1.265</td>
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</tbody>
</table>

B1-SAM

<table>
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<th>A1B-RMSEMM</th>
<th>B1-SAM</th>
<th>B1-RMSEMM</th>
</tr>
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<td>India</td>
<td>Europe</td>
</tr>
<tr>
<td>Suitable land for Agriculture</td>
<td>5.579</td>
<td>2.686</td>
<td>1.112</td>
<td>1.896</td>
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B1-RMSEMM
Table 3.4 Net potential arable land for projected scenarios
(Unit: million km²)

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<th>Russia</th>
<th>South America</th>
<th>U.S.</th>
<th>Global</th>
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<td>Protected land</td>
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<td>0.27</td>
<td>0.75</td>
<td>1.57</td>
<td>4.14</td>
<td>2.41</td>
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<tr>
<td>Human settlement</td>
<td>0.600</td>
<td>0.428</td>
<td>0.484</td>
<td>0.148</td>
<td>0.035</td>
<td>0.145</td>
<td>0.121</td>
<td>2.745</td>
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<tr>
<td>Actual cropland</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2007)</td>
<td>2.47</td>
<td>1.53</td>
<td>1.73</td>
<td>1.21</td>
<td>1.23</td>
<td>1.26</td>
<td>1.73</td>
<td>15.54</td>
</tr>
</tbody>
</table>
| Net potential arable land
| A1b-SAM          | 8.474  | 5.281 | 2.003 | 2.447  | 2.706  | 5.647         | 3.456| 38.052 |
| A1b-RMSEMM       | 7.138  | 4.769 | 2.018 | 2.429  | 3.049  | 6.761         | 3.204| 37.624 |
| B1-SAM           | 9.263  | 5.087 | 2.048 | 2.654  | 2.349  | 7.164         | 3.782| 40.615 |
| % of net available land
| A1b-SAM          | 29.146 | 28.971| 86.376| 49.453 | 45.452 | 22.312        | 50.060| 40.839 |
| A1b-RMSEMM       | 34.601 | 32.081| 85.734| 49.819 | 40.339 | 18.636        | 53.998| 41.303 |
| B1-SAM           | 26.664 | 30.076| 84.478| 45.595 | 52.359 | 17.588        | 45.745| 38.262 |

Sources and Notes
Table 3.5 Rainfed + irrigated land estimate (Unit: million km$^2$)

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<tr>
<td>Suitable land</td>
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<td>2.200</td>
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<td>1.539</td>
<td>0.263</td>
<td>2.900</td>
<td>2.205</td>
<td>21.460</td>
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<td>Marginally suitable land</td>
<td>6.832</td>
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<td>1.327</td>
<td>1.235</td>
<td>2.066</td>
<td>7.012</td>
<td>2.249</td>
<td>29.034</td>
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<td><strong>A1B-SAM</strong></td>
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<td></td>
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Table 3.6 Comparison of simulated baseline results with other studies
(Unit: million km$^2$)

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<th>South America</th>
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<tr>
<td>Suitable agricultural land</td>
<td>5.258</td>
<td>1.885</td>
<td>1.177</td>
<td>2.219</td>
<td>2.793</td>
<td>2.037</td>
<td>19.693</td>
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<tr>
<td>Marginally suitable land</td>
<td>6.854</td>
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<td>1.543</td>
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<tr>
<td>Potential Arable land</td>
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<tr>
<td>Arable land &amp; Permanent crops</td>
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<td>1</td>
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<td>Permanent meadows and pastures</td>
<td>8.85</td>
<td>3.01</td>
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<td>1.38</td>
<td>4.11</td>
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<tr>
<td>Agricultural Area</td>
<td>10.71</td>
<td>4.02</td>
<td>1.81</td>
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<td>4.3</td>
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<td>Cropland</td>
<td>2.78</td>
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<td>Pasture land</td>
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<td>Agricultural land</td>
<td>11.51</td>
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<td>1.92</td>
<td>5.46</td>
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<tr>
<td>Potential arable land</td>
<td>7.5</td>
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<td>2.9</td>
<td>2.0</td>
<td>7.3</td>
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<td>FAO-1994</td>
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<tr>
<td>Potential Arable land</td>
<td>11.10</td>
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<td>3.84</td>
<td>10.48</td>
<td>3.54</td>
<td>41.4</td>
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</table>
Sources: FAO-STAT data are from FAO website (2009); Ramankutty 2000 data are from Ramankutty et al., 2008; Ramankutty 1961-1990 simulated numbers are from Ramankutty et al., 2002; FAO 1994 values are from FAO report (2000)

Table 3.7 Lands suitable for biomass under historic and projected scenarios
(Unit: million hectares)

<table>
<thead>
<tr>
<th></th>
<th>Africa</th>
<th>China</th>
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<td>52</td>
<td>30</td>
<td>19</td>
<td>62</td>
<td>98</td>
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<td>436</td>
</tr>
<tr>
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<td>19</td>
<td>50</td>
<td>105</td>
<td>44</td>
<td>421</td>
</tr>
</tbody>
</table>

FIGURE 3.1 Monthly global mean temperatures under 5 scenarios
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**Humidity Index for 1961-1990**

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(Source: Trabucco and Zomer, 2009)
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![Humidity index membership function]

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![Soil temperature regime membership function]

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Global Humidity Index Changes Aggregated by Climate Zones (SAM) (A1B)

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Global Humidity Index Changes Aggregated by Climate Zones (RMSEMM) (B1)
CHAPTER 4

CONCLUSIONS

This thesis uses several global databases, including soil properties, slope, temperature and precipitation to simulate the land suitability under both current and projected climate by GCMs. Simulations of thirteen GCMs are selected and assembled through two ensemble approaches, Simple Average Method (SAM) and Root Mean Square Error Ensemble Method (RMSEMM), to abate the uncertainty involved in GCM projections. Two emission scenarios, A1B & B1, which represent relatively high and low emission, respectively, are included and analyzed. Fuzzy logic, which handles land classification in an approximate yet efficient way, is adopted to estimate the land suitability through empirically determined membership functions and fuzzy rules chosen through a learning process based on remote sensed crop land products. Land suitability under five scenarios, which are the baseline scenario with the present climate, A1B-SAM, A1B-RMSEMM, B1-SAM, and B1-RMSEMM, is assessed for both global and seven important agricultural regions in the world. The change patterns of climatic factors and land suitability are explored and analyzed.

4.1. FINDINGS

Under the four simulated scenarios, namely, A1B-SAM, A1B-RMSEMM, B1-SAM and B1-RMSEMM, global temperature expects obvious increase by the end of this century, especially at the high latitudes of the north hemisphere. The intra-year distribution of precipitation is likely to be more even, indicating more precipitation from September to next May but less from June to August. Regions including Eastern part of South America, southeast U.S., south Europe, and north and west Africa may experience reduction in precipitation, whereas the north high latitudes expect precipitation increases. Furthermore, the Humidity Index is likely to decrease in regions close to the equator, such as east of South America, southeast U.S., south Europe, India, south China, Australia, and most of Africa, and rise at the north high latitudes. The global patterns of change in precipitation and Humidity Index (i.e., precipitation over potential evapotranspiration) are similar, given that almost all regions expect various levels of warming, which indicates that the potential
evapotranspiration is likely to increase globally though with different magnitudes. Some regions do not achieve agreement in the change magnitude or pattern in one or more of the three climate parameters over the four scenarios, which may imply that those regions are more sensitive to the development paths and/or the ensemble approaches. Thus, the climate change projections in those regions are subject to larger uncertainty than that covered by this study.

It is found that countries at the high latitudes of north hemisphere are more likely to benefit from climate change, while countries at mid- and low latitudes may suffer different levels of loss of potential arable land. The estimated global gross potential arable land under 1961-1990 climate is 49.7 million km$^2$. The projected global changes rely on the emission scenarios (related to the development paths) and ensemble approaches; irrigation improves the total suitable land area for agriculture, yet only to a small extent. Under A1B scenarios, the global gross potential arable land is likely to have a reduction of 0.5~0.8 million km$^2$ while under B1 an expansion of 1~1.2 million km$^2$ may be expected. Large changes are expected for individual regions. Africa and South America have the largest potential arable land, accounting for more than 40% of the world. However, shrinking can be expected due to climate change, by 0.5% ~ 18% and 1% ~ 20% respectively; while reductions are also expected in Europe and India by 11%~17% and 1.7%~3.6%. Expansions of the gross potential arable land are likely to occur in regions at the north high latitudes, like Russia, North China and U.S. by 37%~67%, 4%~17% and 23%~36% respectively. The growth of the potential arable land in those regions mainly attributes to the increased temperature and/or improved Humidity Index which previously constrained the suitability.

The net potential arable land assessed by excluding human settlement land and protected land is 41.3 million km$^2$ under the baseline scenario, and is likely to decrease by 0.7~3.7 million km$^2$ in the projected scenarios. The greatest potential for agricultural expansion lies in Africa and South America, with current cultivated land accounting for less than 20% of the net potential arable land. This result has also been identified by previous studies (FAO, 2000; Ramankutty et al., 2002). Climate change,
and population growth along with the expansion of the protected land may lead to the reduction of the net potential arable land in Africa, South America, India and Europe; increases are likely in Russia, China and U.S., which will mainly benefit from the climate change. China, in particular, has increased potential for further agricultural development in future scenarios, with an increase of around 30% of the current net arable land being cultivated.

4.2. LIMITATIONS

SRES scenarios do not provide the probability of the outcomes (McKibbin et al., 2004). Thus, SRES scenarios still cannot project future changes in climate accurately (Schmidhuber and Tubiello, 2007). In addition, the resolution of the GCM simulations is coarse compared to other databases adopted here, which will affect the quality of outputs.

This work may overestimate the potential arable land attributing to three aspects. Firstly, the definitions of the membership functions do not take extreme events into consideration, like droughts and flooding. In reality, if the temperature is beyond the optimal condition, it generates negative impacts on plants (Olesen and Bindi, 2002). Moreover, if the Humidity Index is too high, it may also hamper the development of crops. However, these are not reflected in the membership functions of air temperature and Humidity Index. Secondly, the climate related parameters, air temperature and Humidity Index, have some deficits to represent the climate influences on land suitability. The annual-average air temperature and HI can not accurately reflect the temperature and water availability for plants in the growing season. Nevertheless, collecting data of the growing season for different regions globally involves heavy work, which is beyond the scope of this thesis. Thirdly, the possible shrinking of the land surface due to sea level rise is not considered in this study, and the land area is assumed to remain the same.

In addition, GCMs may have some biases in their simulations (Ramankutty et al., 2002). However, the ensemble of thirteen GCMs should at least partially offset the biases. If more accurate climatic information is needed, it can be obtained by supplementing the changes between simulated 2070-2099 and simulated 1961-1990 to
the observed 1961-1990 climate data (Ramankutty et al., 2002).

Currently, this work assumes that the fuzzy rules determined from the learning process of the historical landcover map and the membership functions based on empirical knowledge remain applicable in the future. These derived relationships may not remain valid in a different climate future. However, such information is still valid, since no information is available in terms of the future.

The potential arable land estimated by the fuzzy logic provides an approximate, broad view of the probability that the land can be cultivated. The global large scale simulation limits the accuracy of the results for regional analysis. Nevertheless, this work intends to present the main patterns and trends of the distribution of the potential arable land and the possible climate change impacts on it, rather than accurate simulation or prediction of the probable changes for a smaller scale. Based on the results along with comparison with other studies, reliable outcomes have been achieved that can be used as reference for decision making and further applications.

4.3. FUTURE WORK

The classification of the potential arable land is simply a measurement of the land arability. It cannot provide exactly the ultimate productivity of the land, which is largely determined by other management choices (Ramankutty et al., 2002). Although climate change may benefit some regions at the high latitudes and lower the land suitability in some tropical regions, the effects on the actual yield of crops are not simulated here. Thus, in the future, an inclusion of the crop yield simulation can help explore the crop productivity.

Improvements can be made by including the physical representation between the soil characteristics and climate factors. In addition, soil erosion and salinization could be incorporated into the land assessment which may also contribute to land suitability loss (Ramankutty et al., 2002).

Furthermore, more accurate estimates for small scale regions may be achieved through refiner analysis. The methodology could be applied as long as higher resolution data are available. Additionally, if more information, like the growing season data can be accessed, it would certainly improve the estimate’s accuracy of
land arability.

Many applications can be explored based on this study. More comprehensive food security analysis can be achieved if crop yield simulation and economic models including food trade are added. Adaptation decisions and related policies can be made on the basis of the findings. In summary, this study provides valid and comprehensive estimates of potential suitable land under current and projected climate conditions, and can serve as a reliable basis for future studies.
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