

Chapter 2

Land Use Change Dynamics Model Compatible with Climate Models

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Land Use/Cover Change (LUCC) is an important part of the global environmental change, which has always been the scientific hot spot. There are two primary factors that contribute to climate change: land use change and greenhouse gas emission (Kalnay and Cai 2003). This chapter focuses on the Land Use Change Dynamics (LUCD) model which can be compatible with climatic models, including three sub-modules, namely economic module, vegetation change module, and agent-based module.

Firstly, the economic module is capable of estimating the demand of land use changes in economic activities and maximizing economic utility. In this sense, Computable General Equilibrium (CGE) modeling approach can include land as a production factor into the economic module. Second, vegetation change module provides the probability of vegetation change driven by climate change. The Agro-ecological Zone (AEZ) model is supposed as the optimal option for constructing the vegetation change module because it is naturally correlated with AEZs facilitating the coupling of economic module and vegetation change module. Third, the agent-based module identifies if the land use change demand and vegetation change can be realized and provides the land use change simulation results, which are the underlying surfaces needed by Regional Climate Models (RCMs). By importing the RCMs' simulation results of climate change and providing the simulation results of land use change for RCMs, the LUCD model would be compatible with RCMs.

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On the other hand, the climate model is an effective tool to study LUCC on surface climate, but how should it be applied to the research on the regional effects of LUCC? The framework of LUCD model compatible with RCMs is introduced in this chapter. Framework and modules of LUCD models are introduced in the first part. The Weather Research and Forecasting (WRF) Model, as a next-generation mesoscale numerical weather prediction system, is explained in detail in the second section.

The land use simulation model is an important tool to analyze the LUCC, which plays a key role in influencing the global climate. However, there have been few global LUCC simulation models, especially these that can be used to analyze the interaction among the socioeconomic development, climate change and LUCC. The Global Change Assessment Model (GCAM) and the GTAP-AEZ model take account of the influence of social economy and climate change at the global scale, but they may have some parameter errors due to the rough parameter setting. This study aims to compare the simulation results obtained with the GCAM model and GTAP-AEZ model and optimize their parameters according to the specific conditions of China, presented in the last section.

2.1 LUCD: Framework and Modules

LUCC is an important part of the global environmental change, which has always been the academic hot spot. Many simulation experiments have proven that the simulation results of RCMs are sensitive to underlying land use and land cover changes (Shepherd et al. 2010). While the interaction between land use change and climate change has been fully realized, most RCMs introduce LUCC data exogenously (Cai et al. 2010). Always, they apply the LUCC data of one year of history as underlying surfaces and keep them constant ignoring the interaction between LUCC and climate variations. This section provides a framework of LUCD model compatible with RCMs to introduce parameterized LUCC into regional climate change modeling endogenously. Several suggested models are introduced and some specific parameter processing approaches are explained in detail. This modeling framework helps to enhance the understanding of the coupling mechanism of land use system and climatic system, and strengthen the simulation capability of land system.

Land system is geographically complex, which is composed of natural factors, human land use activities, and other impact factors (GLP 2005). Land use change simulation is a prediction of when, where, why, and how land use pattern changes (Deng et al. 2010a, b). However, studies on land use change processes are often challenged by the complex and unexpected human activities and natural constraints. Land use change emerges from the interactions among various components of the coupled human-landscape system and feeds back to the subsequent development of these interactions (Le et al. 2008). Most land use change simulation models simulate successional pattern change of land use under the macro background of the regional population growth, economic development, social progress, changes in the natural environment, and other facts (Liu and Deng 2010).

On the whole, the land use change simulation models can be broadly divided into three major categories: empirical statistical model, agent-based model (ABM), and raster neighborhood relationship-based model (Liu et al. 2005a, b).

There are abundant empirical statistical models applied in land use change simulation. This kind of models can be broadly divided into two categories: econometric model that describes the process of land use change by establishing equations between land use and its influencing factors, and mechanism model identifying the relationship of land use change and its driving factors at grid levels. A typical example of the latter is the Conversion of Land Use and its Effect at Small regional extent (CLUE-S) model whose application in land use change simulation is currently in the ascendant (Veldkamp and Fresco 1996). The CLUE-S model is constructed to simulate land use change and its effects on environment at meso-micro scale. It has the capability of synchronously simulating the changes of multiple types and introduces the dynamic driving factors (such as population and economic growth) to improve the simulation accuracy.

Since the 1990s, along with the rapid development of complexity science, ABM began to be applied in land use change research. The Agent-based Models of Land Use and Cover Change (ABM/LUCC) was specially discussed by LUCC Report No.6, in which the development prospect of ABM in land use change simulation is highly valued (McConnell 2001). The ABM can be divided into two categories. One is simulation model of landscape scale mainly based on traditional spatial modeling techniques and the other depicts human decision-making processes and their interactions (Semboloni et al. 2004; Zhang et al. 2013). The latter mainly identifies the linkage between agents and environment by describing the interaction and affiliation of independent agents (Manson 2006). It is found that the agents would get more benefits under the scenario without climate changes in the long term, even though the total income is lower than that of under the scenario with climate changes. Studies showed that ABM is efficient in describing the interaction between macro individual and micro individual.

As a representative of raster neighborhood relationship-based model, CA model is widely used in land use change simulation, especially urban expansion. Syphard et al. (2005) analyzed the distinction of LUCC caused by urban expansion in areas with different slope with the CA model. One of the superiority of the CA model in land use change simulation is that it supports visualization of the simulation process. The structure of the CA model makes it difficult considering the impacts of land use policies. By combining ABM and Cellular Automata (CA) model, the simulation of land use change is characterized by multi-scale and becomes more effective in multi-objective decision making.

The existing models including CLUE-S model, ABM, and CA model are not compatible with RCMs. The CLUE-S model needs an input of the land use structure and ignores the influences of climate zone change on land use change. The ABM and CA model is good at urban expansion simulation but vegetation change driven by natural environment condition change. In this study, we developed a LUCD model in compatible with RCMs to describe the interdependencies and feedback mechanisms among social economics, ecosystem environment as

well as irrational decision making process. The LUCD model describes a combined and complex system composed of social economic, ecosystem components, and decision making process and consequences. It provides a consistent and comprehensive framework of land use change modeling and emphasis on how the models work together. By introducing Agro-ecological zone (AEZ) based on the simulation results of RCMs, the LUCD model is compatible with RCMs and constitutes an iterative simulation system of LUCC and climate changes.

2.1.1 Land Use Change Dynamics Model

2.1.1.1 Model Structure

LUCD model constitutes of three modules, namely economic module, vegetation change module, and agent-based module. The economic module calculates the land demand for all economic activities maximizing economic utility of land uses. The vegetation change module provides the probability of vegetation change driven by climate changes. And the agent-based module identifies that if the land demand and vegetation change can be realized and provides the land use change simulation results, which are the underlying surfaces needed by RCM. To feed the LUCD model results into RCMs, the land use system applied in the LUCD model should be consistent with the underlying surfaces used in RCMs (Fig. 2.1). By iteratively using the output of one model as the input of another, the LUCD model is compatible with RCMs. In Fig. 2.1, the dotted lines show the data transmission between the LUCD model and RCMs, while the solid lines stand for the flow of information in the LUCD model. The LUCD model provides the simulated land use for RCMs as underlying surface data, then RCMs can simulate the climate change resulted from the land use change. The results of climate change simulated by RCMs are further imported into the LUCD model, affecting land use change.

The economic module estimates the land use change demand driven by human activity. The current condition of land uses are introduced into this module as one of the limitations of economic activities as well as land use decisions. The equilibrium of markets determines the commodity supply and in turn influences the land use demand. Combining the land use demand, the limited amount of land as well as the current land use status, the land use change demand is obtained. The vegetation change module describes the possible vegetation change driven by climate change. The AEZ is the key concept that links the climate change and vegetation change and helps to couple human activity with climate change. The climate change leads to change of AEZs, which determines the growth of vegetation (Stehfest et al. 2007). Consequently, the climate change affects not only the evolution of natural vegetation but also the human activities including planting and breeding. By overlying the AEZs on the current vegetation pattern, the suitability of vegetation change can be evaluated. The agent-based module describes the procedure of land use decision coupled with the land use change demand and

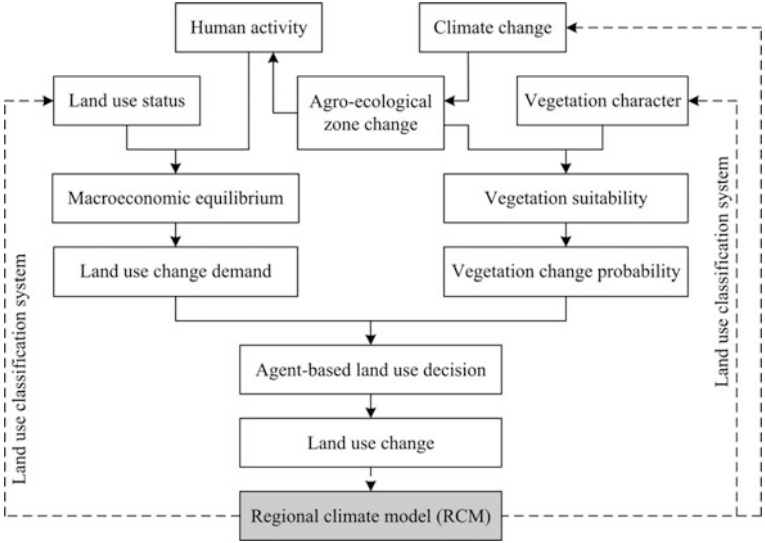


Fig. 2.1 Framework of feeding LUCD model results into RCMs simulation

vegetation change suitability using the agent-based simulation technology. This module identifies whether or not the theoretical land use change demand and the possible vegetation change estimated by the economic module and the vegetation change module can be realized. The output of this module, land use change, is the underlying surfaces that are needed by RCMs. By embedding the LUCD in RCMs, an iterative simulation system of land use change and climate change is constructed (Fig. 2.1).

2.1.1.2 Economic Module

The economic module should provide a comprehensive macroeconomic framework to describe market-oriented economies. CGE model is suggested to be appropriate for such a macroeconomic framework. For convenient application, the way that induces land into the economic module under a CGE modeling framework is proposed as well in this study (Fig. 2.2). Land is one of the three primary factors input in commodity production. And there are five components: producers, households, government, trade, and markets in CGE model. Producers decide demand of inputs including primary factors of land, labor, and capital, and supply of outputs (commodities) to maximize their profits. Households decide demand of commodities and supply of their endowments of labor and capital to maximize their economic utility. Government imposes taxes and expends them in public consumption and savings. The savings of government and households transform into investment according to reserve requirements, which is also an important component in demand. And we employ the small-country assumption that the

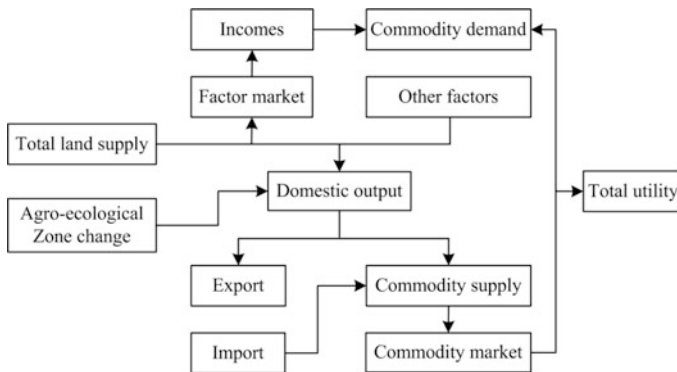


Fig. 2.2 Overview flow chart of economic module applying a CGE modeling framework

study area is too small to affect prices in international markets. Thus, import and export prices, which this country faces, are given for it in foreign currency terms. The demand and supply of commodities and primary factors are equilibrated in markets by price adjustment. With this module, we can compute land uses in various equilibriums to simulate what will happen in the future.

Though CGE models are good at describing the quantities and prices variation as others, we do not introduce land prices but land area in the economic module. This is because the land prices vary along with not only time but also location and productivity, etc. And as a macroeconomic model, CGE model do not support a diverse prices modeling framework. Thus, we summarize land uses in economic development as follows.

$$Y_{i,e} = b_{i,e} \prod_h F_{h,i,e}^{\beta_{h,i,e}} \prod_l Aec_{l,i,e}^{\zeta_{l,i,e}} \quad (2.1)$$

$$Aec_{l,i,e} = \frac{\zeta_{l,i,e} Y_{i,e}}{b_{i,e}} \quad (2.2)$$

where, i is the index of commodities; e is the index of AEZs; l is the index of land use type; h is the index of primary factors (labor and capital); $Y_{i,e}$ is the value added of the i th firm in the e th AEZ; $Aec_{l,i,e}$ is the input area of the l th land use type for i th commodity production in the e th AEZ; $F_{h,i,e}$ is the input of the h th factor by the i th firm in the e th AEZ; $b_{i,e}$ is the scaling parameter in production function, also called total factor productivity (TFP); $\zeta_{l,i,e}$ is the share parameter in production functions; and $\beta_{h,i,e}$ is the share parameter in production functions. Considering the value added is proportional to the input land area under the certain technique condition and primary factors input, the input area of each land use type is calculated by Eq. (2.2).

The input land area of each type of land use per unit of each commodity output is inversely correlated with primary factors input besides TFP. Consequently, the

share parameter, $\zeta_{l,i,e}$, is determined by the input of the h th factor by the i th firm in the e th AEZ, $F_{h,i,e}$.

$$\zeta_{l,i,e} = fl, e(Flabor, i, e, Fcaptial, i, e) \quad (2.3)$$

The land demand input in commodity production is determined by the economic system, because the economic links in the comprehensive macroeconomic framework provided by CGE model are tightly connected with each other. Each shock to economic system will influence the area demand of lands input in commodity production. For example, the growth in the rate of direct tax will lead to an increase in government revenues and a decrease in household income. Then, the structure differences of investments and consumptions between government and household determine the change of commodity demand structure. Under the market-clearing condition, the commodity production and supply structure should be altered. And finally, the area demand of lands input in commodity production will change.

As one of the economic models, the economic module assumes that the ultimate purpose of economic development is to increase the economic utility of household. Household's economic utility is dependent on the amount of consumption of commodity, which are purchased from producers.

$$Uec = \prod_i Xp_i^{\chi_i} \quad (2.4)$$

where, Uec is the economic utility; Xp_i is the amount of consumption of the i th commodity; and χ_i is the share parameter in the economic utility function.

The economic utility is indirectly restrained by the area of land used for economic development. In reality, the earnings from endowments of land are the component household's income which is the constraint of household consumption. And the input of land in production by producer determines the output and supply of commodity. Nevertheless, we only consider the constraint function of land in production in this module because the earnings from the endowment of land are not included when accounting income constraints. The economic development can be summarized as the following optimization problem:

$$\underset{\{Ueco, Uent\}}{\text{maximize}} \quad Uec = \prod_i Xp_i^{\chi_i} \quad (2.5)$$

subject to

$$Tland = \sum_e \sum_l \sum_i Aec_{l,i,e} \quad (2.6)$$

where, $Tland$ is the total land area which is exogenously defined. Equation (2.5) shows the objective function of economic utility to be maximized; and Eq. (2.6) is a total land area constraint equation meaning that total land areas used for commodity production must equal to the total land area used in economic activity on

the left-hand side of the equation. The simulated land use change demand at regional scale can be allocated to grids by using DLS model (Deng et al. 2010a, b), CLUE-S model (Verburg et al. 2002) and CA model (Lau and Kam 2005) etc.

2.1.1.3 Vegetation Change Module

The vegetation change module assesses the growth suitability of specific vegetation and provides the possibility of vegetation change. There are many models including Dynamic Global Vegetation Model, Holdridge Life Zone Model, and AEZ model that can be used to describe the vegetation change driven by climate change. In this study, we propose AEZ model as the optimal option because it is naturally correlated with AEZs facilitating the coupling of economic module and vegetation change module. We also illustrate how to estimate the possibility of vegetation change using AEZ model. The AEZ model is developed by Food and Agriculture Organization (FAO) of the United Nations with the collaboration of the International Institute for Applied Systems Analysis (IIASA) (Schmidhuber and Tubiello 2007). Climate, topography, and soil characteristics are three key inputs of the AEZ model. The model can estimate the climate limited vegetation productivity. Assuming that the estimated climate limited productivity of the v th type of vegetation in the pixel p in the t th year is $Y_{v,p,t}$, the possibility of vegetation change of the v th type of vegetation in the pixel p in the $(t + 1)$ th year is

$$P_{v,p,t+1} = \frac{Y_{v,p,t+1} - Y_{v,p,t}}{Y_{v,max}} \quad (2.7)$$

where, $Y_{v,max}$ is the maximum climate limited productivity of the v th type of vegetation; and $P_{v,p,t+1}$ is the possibility of vegetation change of the v th type of vegetation in the pixel p in the $(t + 1)$ th year.

A positive $P_{v,p,t+1}$ implies that the v th type of vegetation in the pixel p will expand or be more thickly forested in the $(t + 1)$ th year, while a negative $P_{v,p,t+1}$ means that the v th type of vegetation in the pixel p will be inclined to degrade in the $(t + 1)$ th year. The possibility of vegetation change provides the comparison criterion of specific vegetation change of different pixel in different time. When comparing the superiority of different vegetation in the specific pixel and time, a superiority index, $S_{v,u,p,t}$ is proposed.

$$S_{v,u,p,t+1} = \frac{Y_{v,p,t+1} - Y_{v,p,t}}{Y_{u,p,t+1} - Y_{u,p,t}} \quad (2.8)$$

where, $S_{v,u,p,t+1}$ is the superiority index of the v th type of vegetation compared with the u th type of vegetation in the pixel p in the $(t + 1)$ th year.

The superiority index cannot depict the dominance relations between two types of vegetation by itself. The application of this index should combine with the possibility of vegetation change. For instance, when $P_{v,p,t+1}$ is positive and

$S_{v,u,p,t+1}$ is larger than 1, the v th type of vegetation is more superior than the u th type of vegetation in the pixel p in the $(t + 1)$ th year. A more exact mathematical formula for judging the dominance relations of multiple types of vegetation is proposed in the agent-based module.

2.1.1.4 Agent-based Module

Determination of land use change is partly characterized by non-rationality such as tradition and custom. The agent-based module identifies if the land use change demand simulated by economic module and the possible vegetation change assessed by vegetation change module can be realized under the background of irrational decisions. Agent-based modeling is able to simulate land use change by measuring the individual behavior and results of land use over time. Take the decision of land use change of a given household for instance. The dissimilarities between a given household h and all defined household groups in the population can be measured.

$$D_{h,g} = \sum_{s=1}^S w_s \left[\frac{(V_{h,s} - \bar{V}_{g,s})^2}{|V_{h,s} + \bar{V}_{g,s}|} \right] \quad (2.9)$$

where, $D_{h,g}$ is the distance from household h ($h = 1, 2, \dots, H$) to the household group g ($g = 1, 2, \dots, G$). $V_{h,s}$ is the value of variable s ($s = 1, 2, \dots, S$) representing the character of household h . $\bar{V}_{g,s}$ is the average value of variable s of households in household group g ; w_s is the weight coefficient of the variable s in explaining the character of household and household group.

The household h is assigned into the most similar household group and makes the same land use change decision with the household group.

$$g' = \arg \min \{D_{h,1}, D_{h,2}, \dots, D_{h,g}, \dots, D_{h,G}\} \quad (2.10)$$

where, g' is the most similar household group to household h . By establishing a case database of land use change decision, we can assign each household into one similar enough household group and deduce the land use decision. It helps correct the land use change results simulated of economic module based on ideas of optimization.

For the assessment result of vegetation change module, the agent-based module also provides a criterion to judge which kind of vegetation change will happen in a specific pixel.

$$L_{v,p} = \begin{cases} 1, & \text{if for } \forall u \neq v, P_{v,p,t+1} > 0 \text{ and } S_{v,u,p,t+1} > 1 \text{ or } \leq 0, \\ & \text{or } P_{v,p,t+1} \leq 0 \text{ and } S_{v,u,p,t+1} > 0 \text{ or } \leq 1; \\ 0, & \text{if for } \forall u \neq v, P_{v,p,t+1} > 0 \text{ and } S_{v,u,p,t+1} > 0 \text{ or } \leq 1, \\ & \text{or } P_{v,p,t+1} \leq 0 \text{ and } S_{v,u,p,t+1} > 1 \text{ or } \leq 0. \end{cases} \quad (2.11)$$

where, $L_{v,p} = 1$ denotes that the v th type of vegetation is the dominant vegetation in the pixel p and $L_{v,p} = 0$ denotes that the v th type of vegetation is not the dominant vegetation in the pixel p . This criterion defines that for any other vegetation type u , when $P_{v,p,t+1}$ is positive and $S_{v,u,p,t+1}$ is larger than 1 or no larger than 0, or $P_{v,p,t+1}$ is not positive and $S_{v,u,p,t+1}$ is smaller than 0 or no larger than 1, the v th type of vegetation is dominant vegetation in the pixel p in the $(t + 1)$ th year; when $P_{v,p,t+1}$ is positive and $S_{v,u,p,t+1}$ is larger than 0 or no larger than 1, or $P_{v,p,t+1}$ is not positive and $S_{v,u,p,t+1}$ is larger than 1 or no larger than 0, the v th type of vegetation is not the dominant vegetation in the pixel p in the $(t + 1)$ th year.

For a specific pixel, vegetation change will happen as long as the productivity of the new dominant vegetation exceeds that of the original dominant vegetation.

$$LV_{p,t+1} = v, \quad \text{if for } \forall u \neq v, \quad RY_{v,p,t+1} > RY_{u,p,t+1} \quad (2.12)$$

$$RY_{v,p,t+1} = RY_{v,p,t} + \frac{RY_{v,p,t}}{RY_{p,t}} Y_{v,p,t+1} \quad (2.13)$$

$$RY_{p,0} = \sum_v \frac{A_{v,p,0}}{A_p} Y_{v,p,0} \quad (2.14)$$

where, $LV_{p,t+1}$ denotes the new vegetation type that characterized the pixel p in the $(t + 1)$ th year. $RY_{v,p,t+1}$ is the productivity of the v th type of vegetation in the pixel p in the $(t + 1)$ th year. $RY_{p,t}$ is the total productivity of all the vegetation in the pixel p in the t th year; $RY_{p,0}$ is the total productivity of all the vegetation in the pixel p in the base year. A_p is area of pixel; $A_{v,p,0}$ is area the v th type of vegetation in the pixel p in the base year; and $Y_{v,p,0}$ is the productivity of the v th type of vegetation in the pixel p in the base year.

2.1.2 Concluding Remarks on LUCD Model

In this part, we introduced the LUCD model which is compatible with RCMs to provide endogenous underlying surface for climate modeling. This model is constituted by economic module, vegetation change module, and agent-based module. The economic module calculates the land use change demand driven by economic activities aiming at maximizing economic utility. The vegetation change module evaluates the probability of vegetation change driven by climate change. These two modules depict the land surface process under the condition of rational decision making and ideal circumstances. To couple the economic module and vegetation change module, the AEZ is introduced in the LUCD model. The agent-based module identifies if the land use change demand and vegetation change can be realized under the condition of irrational decision making and multiple vegetation competition. By introducing the simulation results of the LUCD model in

RCM and applying the simulation results of RCM in the LUCD model, a coupled simulation system of land surface system simulation can be established.

In addition to the modeling framework, several suggested models are introduced and some specific parameter processing approaches are explained in detail for the constitution of the LUCD model. For the economic module, a CGE modeling framework and the difference between land and other production factors in CGE model are introduced. The effects of climate change on human activities are also taken into consideration by establishing production function for each AEZ. The AEZ model is suggested for the vegetation change module and two indexes (possibility of vegetation change and superiority index) are supposed to determine the climate-induced vegetation change. For the agent-based module, an example of land use change decision making and the criterion of vegetation change is provided.

To ensure the output on LUCC of LUCD model easily feed into RCMs, the classification system of LUCC should be comparable with that needed by RCMs as underlying surface. The classification system determines the choice of driving factors that affect land use change, vegetation change as well as decision making processes in the LUCD model. And the specific parameter processing approaches provided in this study can also serve as valuable examples even if a new modeling approach is used in the LUCD model.

2.2 Weather Research and Forecasting Model

With the development of the climate models and land surface process models, the numerical simulation has become widely used to study the influence of LUCC on climate. The WRF Model is a next-generation mesoscale numerical weather prediction system designed to serve both atmospheric research and operational forecasting needs. It features two dynamical cores, a data assimilation system, and a software architecture allowing for parallel computation and system extensibility. The model serves a wide range of meteorological applications across scales ranging from meters to thousands of kilometers. The effort to develop WRF model began in the latter part of the 1990s and was a collaborative partnership principally among the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration,¹ the Air Force Weather Agency (AFWA), the Naval Research Laboratory, the University of Oklahoma, and the Federal Aviation Administration (FAA).

¹ National Oceanic and Atmospheric Administration are represented by the National Centers for Environmental Prediction (NCEP) and the (then) Forecast Systems Laboratory (FSL).

WRF model allows researchers to produce simulations reflecting either real data (observations, analyses) or idealized atmospheric conditions. WRF model provides operationally forecasting, flexible and computationally efficient platform, offering advances in physics, numerics, and data assimilation contributed by many research community developers. WRF model is currently used at National Centers for Environmental Prediction (NCEP), the AFWA, and other centers.

2.2.1 Development of WRF Model

WRF model has a large worldwide community of users (over 20,000 in over 130 countries), and workshops and tutorials are held each year at NCAR. There are two dynamical core versions of WRF model, each with its own web page. The Advanced Research WRF (ARW) is supported to the community by the NCAR Mesoscale and Microscale Meteorology Division.² The WRF-NMM (NMM) is supported to the community by the Developmental Test bed Center (DTC).³ The development of WRF model with ARW dynamic core is shown in Table 2.1.

The ARW model represents the latest developments following a particular modeling approach that uses time-splitting techniques to efficiently integrate the fully compressible nonhydrostatic equations of motion. The ARW is suitable for use in a broad range of applications across scales ranging from meters to thousands of kilometers. The main application includes idealized simulations (e.g., LES, convection, baroclinic waves), parameterization research, data assimilation research, forecast research, and real-time NWP. Besides, hurricane research, regional climate research, coupled-model application as well as teaching.

The Mesoscale and Microscale Meteorology Division of NCAR is currently maintaining and supporting a subset of the overall WRF code. The WRF modeling system software in the public domain is freely available for community use. The WRF modeling system consists of four important major programs, which are WRF Preprocessing System (WPS), WRF-DA, ARW solver, and the post-processing and visualization tools.

2.2.2 Application of WRF Model

WRF model is mainly applied to the weather and climate research when horizontal resolution is 1–10 km. It can also be applied to numerical simulation, physical parameterizations research, data assimilation, numerical ideal test and provide meteorological field for air quality model.

² For detailed information: <http://www.mmm.ucar.edu/wrf/users>.

³ For detailed information: <http://www.dtcenter.org/wrf-nmm/users>.

Table 2.1 Development of WRF model with ARW dynamic core

Version	Release time	Note
WRF V1.0	2000.11	The first version was released
WRF V1.1.1	2001.11	The third version was released. WRF V1.1 was not changed much, except for two error revision
WRF V1.2	2002.4	The fourth version was officially released. Then V1.2.1 was released in May 22nd
WRF V1.3	2003.3	
WRF V2.0	2004.5	The nested versions was released, including single and double nested and 3-dimensional variational data assimilation system (3DVAR), and NMM was added and EM nesting was released
WRF V2.1	2005.8	EM becomes ARW
WRF V2.2	2006.11	WRF preprocessing system (WPS) was issued to replace the WRF standard initialization (WRF SI), and WPS was released
WRF V3.0	2008.4	WPS has been used, adding global ARW version
WRF V3.1	2009.4	
WRF V3.2	2010.4	
WRF V3.3	2011.4	4DVAR was updated
WRF3.4	2012.4	QNSE PBL method was added, as well as the Noah MP(multi-physics) land surface model, and variation of sea-ice albedo with T were allowed, thus, Noah and Noah MP were in new shared sea-ice module. Sfclay option 1 code was modified and cleaned up.
WRF3.5	2013.4	New land-surface models such as RUC LSM, PX LSM, and CLM4 land were included.

The key consideration of WRF model is to forecast the important weather process from the cloud scale to the synoptic scale, including pre-processing module WPS (WRF processing system) and main module ARW. WPS is not only the pre-processing part of mode data, but also the part that provides some initial boundary before the three-dimensional variation systems established. It is mainly responsible for the standard grid data preprocessing and terrain data preprocessing. WPS modules include three sub-modules: geogrid, ungrib, metgrid. Among them, main function of geogrid is to define and create land patterns. In the geogrid module, users can set the projection domain, range size, regional location, nesting, and other parameters. According to these custom settings, geogrid will interpolate topography, land use, soil type, and other data to the defined region network, the data format is NetCDF. Ungrib module's main function is converting standard grib files into ones that can be recognized by metgrid. Typically grib files have many different formats; the same meteorological elements may have different elements code. For these different formats, WPS provides the corresponding Vtable function pointer, such as AWIP, GFS, etc. Metgrid module is for meteorological data interpolation. It interpolates the meteorological of large area into calculated grid of

pattern (including the horizontal direction and the vertical direction), and provides initial and boundary condition file for the model.

In WRF model, the original land use data come from the global 24 types of land use and land cover classified by United States Geographical Survey land use systems (USGS). Each land use types have different roughness, albedo, and other parameters, affecting the flow of meteorological fields, precipitation, temperature, or temperature.

In WRF simulation, each grid point has a land cover type based on the land cover dataset being used for the model run. The properties (surface albedo, surface emissivity, moisture availability, surface roughness length) of each land cover type depend on the land surface model used in the WRF run. The land-surface model is the component that takes care of the processes involving land-surface interactions. For the WRF runs, the parameterization scheme of physical processes in the model should be set, USGS classification data set need to be used to specify land cover types and their properties.

The interactions between the atmosphere and other earth system components, which are important drivers of regional climate, are not well explained in most RCMs models. Although more and more of these interactions are now represented in GCMs, global models lack the spatial resolution to represent regional-scale processes and feedbacks. Biases in simulating regional precipitation, for example, can have far-reaching consequences in fully coupled models of the climate system, because water integrates across the physical, biological, and chemical components.

Therefore, WRF is strongly recommended to address a wide range of science questions specific to regional-scale processes, and forcing and response. Examples include interactive coupling of the RCM with sea ice and ocean models to represent air–sea interactions; chemistry and aerosol models, including dust, to represent chemistry–aerosol–cloud–radiation feedbacks; and marine and terrestrial ecosystem models to represent biogeochemical cycling processes. Additionally, developing more comprehensive treatments of land surface and hydrological processes, including river routing, subsurface flow, lake, land use, fires, and land ice, will enable a more dynamic representation of land–atmosphere feedbacks. It is noted that some development efforts are already underway in the framework of the Community Land Model (CLM) and Noah land surface model that have been implemented in WRF. Building data assimilation capabilities for the coupled model will enable the development of regional analyses of the Earth system; an example is an ocean and land data assimilation system. Finally, to facilitate model coupling, participants recommended accelerating the transition of WRF to the Earth System Modeling Framework (ESMF) (Tolstoy et al. [2004](#)).

2.3 Global Models Combining Emission Scenarios with Land Use Changes

The land use simulation model is an important tool to analyze the LUCC, which plays a key role in influencing the global warming. However, there have been very few global LUCC simulation models, especially the models that can be used to analyze the interaction among the socioeconomic development, climate change, and LUCC. The Global Change Assessment Model (GCAM) and the GTAP-AEZ model are two models that take account of the influence of social economy and climate change at the global scale, but they may have some parameter errors due to the rough parameter setting. This study aims to compare the simulation results obtained with the GCAM model and GTAP-AEZ model and optimize their parameters according to the specific conditions of China. First, we simulated the land use structure in China in 2010 with the two models and compared the simulation results with the real one. Second, we calibrated these parameters of models according to the China's national conditions and implemented the simulation again. The result indicates the calibrated GCAM can provide more accurate simulation result of land use, which can provide significant reference information for the land use planning and policy formulation to mitigate the climate change in China.

2.3.1 Overview of Global LUCC Simulation Models

Humans have transformed significant portions of the Earth's land surface, 10–15 % of which is currently dominated by agricultural crop or urban-industrial areas, and 6–8 % is pasture (Vitousek et al. 1997). These land use changes have important implications for future climate changes, and consequently, great implications for subsequent land use changes (Deng et al. 2013; Nunes and Auge 1999; Turner 1994). Climate change and land use change are both global driving forces of environmental change, and the impact assessments generally show that interactions between them can lead to serious challenges to the provision of ecosystems services. Besides, in many cases it is impossible to determine the impacts of climate change without consideration of LUCC. LUCC is a widespread, significant, and accelerating process, and it has been one of the research cores of the international programmes, such as the International Geosphere-Biosphere Programme (IGBP) and the Global Environmental Change Human Dimensions Programme (IHDP) and is also one of the global environmental research focuses and cutting-edge issues (Liu and Deng 2010). LUCC is driven by human activities, and in many cases it also leads to changes that impact the humans, therefore, LUCC modeling is a critical way for formulating effective environmental policies and management strategies (Jiang et al. 2012). Understanding the role of land use change in the global environmental change requires the analysis of historical land

cover conversions and projection of possible future land use changes, both of which heavily rely on the land use simulation models. Besides, the land use simulation model also provides an essential approach for stakeholder to project and evaluate the potential consequences of policy decisions and other actions. As more scholars realized the importance of LUCC, the land use simulation model has become an important tool for the analysis of both the mechanism and the spatial distribution of LUCC in the past and future (Deng et al. 2012; Hu et al. 2004).

The land use simulation models include Markov model, logistic function model, regression model, econometric model, dynamic systems model, spatial simulation model, linear planning model, nonlinear mathematical planning model, mechanistic GIS model, CA model, and so on (Flamenco-Sandoval et al. 2007). All of these models may help to explore the combined effects of social policies, individual behavior, and other drivers of the land use change, however, most of them have some drawbacks. For example, the Markov model has been widely used to simulate the land use change, but it involves no spatial factors, so the land use change cannot be spatially explicitly reflected. The CLUE-S model can comprehensively analyze the regional LUCC process and driving force, but it can only be used in the spatial allocation so far, while the nonspatial changes must be estimated with other methods (Deng et al. 2008). Therefore, although some models can be used to simulate land use change, there are still some serious drawbacks (Liu and Deng 2010; Cai et al. 2004). Moreover, there were few global models to simulate the LUCC, especially in the study of the interaction mechanism among the social economy, climate change, and LUCC. In some sense, the GTAP-AEZ model and the Global Change Assessment Model (GCAM) are more useful in the land use simulation, which can simulate the land use change of each agricultural ecological zone (AEZ), combined with the influences of social economy and climate change at global scale (Sands and Leimbach 2003; Lee 2004; Burniaux and Lee 2003). However, the parameters of these models are rough and the simulation accuracy needs to be improved.

In the preparation for the fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5), the international community is developing new advanced Earth System Models (ESMs) to address the combined effects of human activities (e.g., land use and greenhouse gas emissions) on the carbon-climate system. Besides, the four Representative Concentration Pathways (RCPs) scenarios of the future (2005–2100) have been provided by the four Integrated Assessment Model (IAM) teams, which are used as input to the ESMs for the future carbon-climate projection (Moss et al. 2008; Moss et al. 2010). This study aims to compare the simulation results of land use change obtained from the GCAM and GTAP-AEZ model and improve the simulation accuracy through optimizing the input parameters of the models, and the calibrated GCAM can be used to provide more scientific reference information of land use change for the land use planning and policy formulation to mitigate the climate change in China.

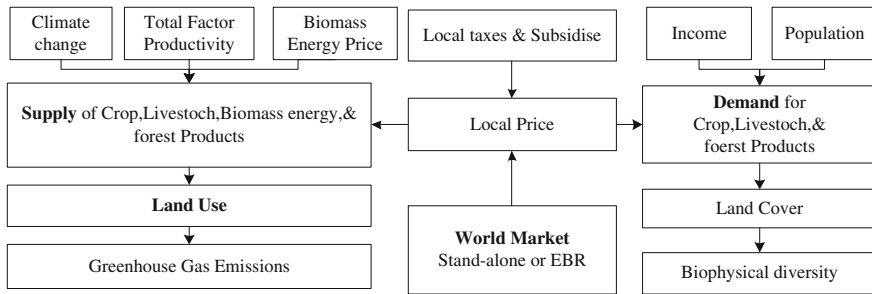


Fig. 2.3 Land use allocation framework of GCAM

2.3.2 Key Methods and Models to Combine Emission Scenarios with Land Use Changes

2.3.2.1 GCAM Model

GCAM is a dynamic recursive model of land use and land cover, economy, agriculture, and energy, which fully integrates the energy and agriculture systems with economic equilibrium in the energy and agriculture markets (Wise et al. 2009). GCAM consists of four modules, i.e., Edmonds-Reilly-Barnes model (ERB) (Edmonds et al. 1997), Agriculture and Land use simulation model (AgLU) (Sands and Leimbach 2003; Thomson et al. 2005), Model for the Assessment of Greenhouse gas Induced Climate Change (MAGICC) (Wigley and Raper 1992), and Regional Climate Change Scenario Generator (SCENGEN) (Hulme et al. 1995). The inputs of GCAM include capital, labor, initial land use allocation, all of which need to be provided by researchers.

The land allocation diagram (Fig. 2.3) shows how land is allocated among alternative land uses types, selection of land use is based on maximizing economic return at a region, profit per hectare is equal to revenue (yield per hectare times price received) less production cost (yield per hectare times nonland cost per unit of output). This relationship is shown in Eq. (2.15)

$$\pi r_{i,l,m,p} = y_{i,l,m,p} \cdot (P_{i,l,m} - G_{i,l,m}) \quad (2.15)$$

where $\pi r_{i,l,m,p}$ is the economic return of the land as a profit rate (\$/ha-yr), $y_{i,l,m,p}$ is yield per hectare for land use i in region j at location p (calories/ha). $P_{i,l,m}$ is the market price for the product produced by land use i (units \$/yield units: calories or m^3). $G_{i,l,m}$ is the non-land cost per unit of output in land use (units are \$/yield units: calories or m^3), i is an index for land use type. l is the region index. p is an index for geographical location within a region.

While calculating profit rate πr of forest products is different somewhat because of the time lag between planting and harvest. The profit rate expression for forest

products includes a term that discounts future earnings into the present; this forward price is denoted by $\bar{P}_{i,l,m}$.

$$\pi r_{i,l,m,p} = \frac{r}{(1+r)^{45}-1} \cdot (\bar{P}_{i,l,m} - G_{i,l,m}) \quad (2.16)$$

where r is the interest rate (\$/\$ that is unitless).

In order to determine the share of land allocated to each land use type, land use shares should be calculated numerically, by summing over the land distributions implied in Eqs. (2.15) and (2.16). We use instead a reduced-form expression for land shares that effectively sums over the index p in Eqs. (2.15) and (2.16) based on maximizing profit rates, which is at the core of finding land shares that provide the yields leading to maximum profits.

With the specific assumptions on the functional form of the yield distribution, the share of land allocated to use i is given by a logit share equation:

$$S_{i,l,m} = \frac{\bar{\pi} r_{i,l,m}^{\frac{1}{\lambda}}}{\sum_p \bar{\pi} r_{i,l,m,p}^{\frac{1}{\lambda}}} \quad (2.17)$$

where λ is a positive parameter that determines the rate that land shares change in response to a change in profit rate. $\bar{\pi} r_{i,l,m}$ is the average profit rate using land use type i , which is the profit rate evaluated at an average or intrinsic yield, \bar{y}_i

Land use for a specific purpose is calculated based on this logit-based share of total land:

$$Landuse_{i,l,m} = S_{i,l,m} \cdot Totalland_l \quad (2.18)$$

2.3.2.2 GTAP-AEZ Model

The GTAP-AEZ model is based on the GTAP-E model, which allows for substitution between capital and energy, and between various fuels in sectoral production. Sectors may substitute energy for capital when the rise of energy price is more than that of the capital rental (Fig. 2.4). The inter-fuel substitution comprises of three sub-nestings: (a) electricity versus non-electricity composite; (b) coal versus non-coal composite; and (c) among oil, gas, and petroleum products. For example, sectors may substitute coal for non-coal fuel (a composite of oil, gas, and petroleum products) when coal is more expensive than non-coal fuels.

Based on the RCP 4.5 scenario, potential future economic activities are assumed. Using this land use model, equilibrium solutions are then found. The inputs used for the production are capital, labor, land, and other intermediate inputs. In the GTAP-AEZ model, we recognize a unique production function for

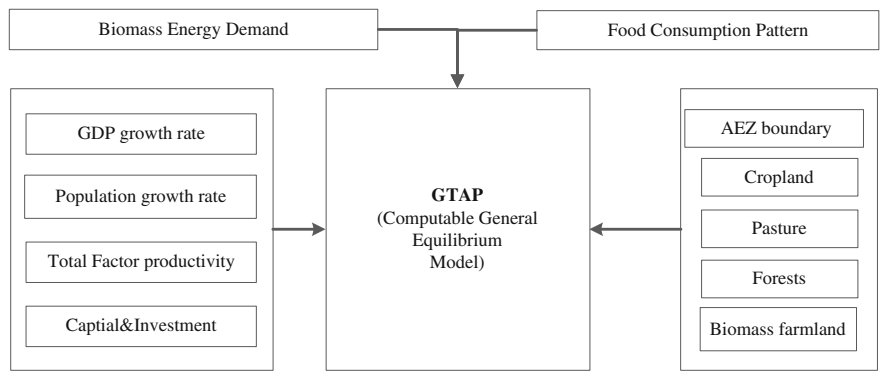


Fig. 2.4 Framework of the GTAP-AEZ model The GTAP-E model is a multisector, multi-region, and recursive dynamic CGE model that extends the standard GTAP model through including the international capital mobility, endogenous capital accumulation, and the adaptive expectations of investment. This model is distinguished for its disequilibrium mechanism of determining the regional supply of investments. This disequilibrium mechanism includes the adjustment of the expected rate of return toward an actual return rate within each region and adjustment of the regional expected return rate toward the global return rate. These lagged adjustment mechanisms, as well as the mechanism of determining the composition of capital and allocation of wealth are parameterized according to the econometric estimation documented by Golub (Golub 2006). In the analysis of the equilibrium of land use, it is assumed that the land is distributed among sectors for the maximization of profits in each period with similar capital and labor, although the land use does not change rapidly

each of the land-using sectors located in a specific AEZ. For example, the paddy rice sector located in AEZ 1 has a different production function from the paddy rice sector located in AEZ 6. This is to identify the difference in the productivity of land of different climate characteristics. Nevertheless, all the paddy rice sectors located in the AEZ6 produce homogenous output to meet market demand.

We assume that transition of land in a specific AEZ can occur only between sectors whose land is appropriate for their use. This is a new concept beyond the standard GTAP model, in which land is assumed to be transformable between uses of crop growing, livestock breeding, or timber plantation, regardless of climatic or soil constraints. Facts show that most plants can only grow on land that is under certain temperature, moisture, soil type, land form, etc. We believe that the introduction of the agro-ecological zoning (AEZ) renders a sound presentation of sector competition for land.

We split the total sector land rent into 18 AEZs according to the AEZ-specific production shares derived from the data provided by the Center for Sustainability and the Global Environment (SAGE) (Lee 2004) as follows.

$$L_{ca} = L_c * \left[\sum_{i \in SAGECROPS=c} P_i * \frac{Q_{ia}}{H_{ia}} * H_{ia} / \sum_{a \in AEZS} \sum_{i \in SAGEROPS=c} P_i * \frac{Q_{ia}}{H_{ia}} * H_{ia} \right]$$

$c \in LANDUSE; i \in SAGECROPS; a \in AEZS.$

(2.19)

where L_{ca} is the land rent accrued to the land use sector c in AEZ a ; L_c is the land rent of the land use sector c , with no AEZ distinction; P_i is the per-ton price of SAGE's land use type i ; Q_{ia} is the production (ton) of SAGE's land use type i in AEZ a ; and H_{ia} is the harvest area of SAGE's land use type i in AEZ a . The $\sum_{i \in SAGECROPS}$ operator means to aggregate over the disaggregated land use type i to the corresponding aggregated land use sector c . Note that we assume the per-ton land production price P_i is homogenous across the AEZs.

2.3.3 Scenarios

The Integrated Assessment Models (IAMs) explored a range of technological, socioeconomic, and policy futures that could lead to particular concentration pathways and magnitudes of climate change, which is represented by the RCPs. The RCPs include four different scenarios (Table 2.2), i.e., one mitigation scenario leading to a very low forcing level (RCP2.6), two medium stabilization scenarios (RCP4.5/RCP6), and one very high baseline emission scenarios (RCP8.5), all of which could be obtained with different combinations of economic, technological, demographic, policy, and institutional futures. The development of the RCPs in the first phase allows climate modelers to proceed with experiments in parallel to the development of emission and socioeconomic scenarios, expediting the overall scenario development process (Moss et al. 2010). Coupled carbon-cycle climate models can then as well calculate associated emission levels (which can be compared to the original emissions of the IAMs) (Hibbard et al. 2007).

Two important characteristics of RCPs are reflected in their names. The word “representative” indicates that each of the RCPs represents a large set of scenarios in the literatures. In fact, as a set, the RCPs should be compatible with the full range of emissions scenarios available in the current scientific literatures, with and without the climate policy. The words “concentration pathway” means to emphasize that these RCPs are internally consistent sets of projections of the components of radiative forcing that are used in subsequent phases rather than the final new and fully integrated scenarios, i.e., they are not a complete package of socioeconomic, emission, and climate projections. The use of the word “concentration” instead of “emissions” also emphasizes that concentrations are used as the primary product of the RCPs and designed as inputs for climate models (Wu et al. 2013).

Table 2.2 Description of RCPs

RCPs	Description	Publication-IA Model
CP8.5	Rising radiative forcing pathway leading to 8.5 W/m^2 in 2100	MESSAGE (Riahi et al. 2007)
RCP6	Stabilization without overshoot pathway to 6 W/m^2 at stabilization	AIM (Y. Hijioka 2008)
RCP4.5	Stabilization without overshoot pathway 4.5 W/m^2 at stabilization after 2100	GCAM (Smith and Wigley 2006)
RCP2.6	Peak in radiative forcing at $\sim 3 \text{ W/m}^2$ before 2100 and decline	IMAGE (Van Vuuren et al. 2006)

The RCP4.5 scenario is a stabilization scenario in which the total radiative forcing is stabilized shortly after 2100, without overshooting the long-run radiative forcing target level (Liu et al. 2005a, b). RCP4.5 includes long-term, global emissions of greenhouse gases, short-lived species, and land use-land cover in a global economic framework which stabilizes the radiative forcing at 4.5 Watts per square meter (W/m^2), approximately 650 ppm CO_2 -equivalent in the year 2100 without ever exceeding that value. The defining characteristics of this scenario are enumerated in Moss' papers (Moss et al. 2008; Moss et al. 2010). RCP 4.5 was updated from earlier GCAM scenarios to incorporate the historical emissions and land cover information and follows a cost-minimizing pathway to reach the target radiative forcing. The necessity to limit emissions in order to reach this target leads to the changes in the energy system, including shifts to electricity, lower emissions energy technologies and the deployment of carbon capture and geologic storage technology. In addition, the RCP4.5 emission price is also applicable to the land use emissions. The simulated future emissions and land use were downscaled from the regional scale to the grid scale to facilitate the transfer to climate models. While there are many alternative pathways to achieve a radiative forcing level of 4.5 W/m^2 , the application of the RCP4.5 provides a common platform for climate models to explore the response of the climate system to stabilizing the anthropogenic components of radiative forcing. Therefore, the RCP4.5 scenario is used in this study, under which the land use change is simulated with GCAM. Besides, the GTAP-AEZ model, which is similar to GCAM, is also used to analyze the land use structure in AEZs, and the results obtained with the two models were finally compared.

2.3.4 Results and Analysis

The results indicate that the land use area in different AEZs, which are obtained with the GCAM model and the GTAP-AEZ model, are generally consistent. The pasture land areas simulated with the two models differ most greatly, but are still generally consistent in different AEZs. Besides, the results obtained with the GTAP-AEZ model and the GCAM model both show that the grassland is approximately equally

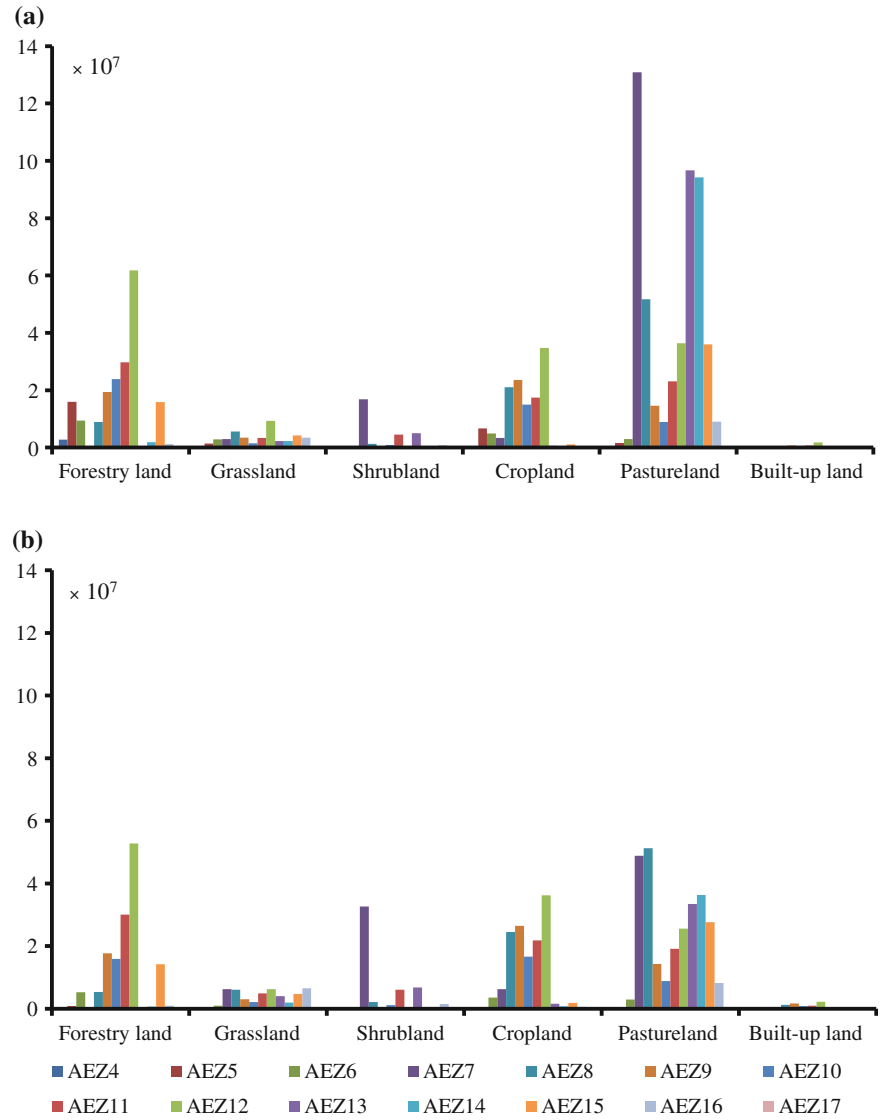


Fig. 2.5 Simulated land use area in 14 AEZs in 2010 using the GCAM model (a) and GTAP-AEZ model (b) (hectare)

distributed in different AEZs, but the grassland area in different AEZs differs a bit more greatly in the result obtained with the GCAM model. In addition, the results obtained with the two models show that the forestland is mainly located in AEZ9-AEZ12, while the shrubland and cropland are mainly in AEZ7-AEZ13. What's more, the built-up land, the area of which is the smallest, is generally distributed in AEZ10 (Fig. 2.5). Comparing the results obtained with the two models, we found

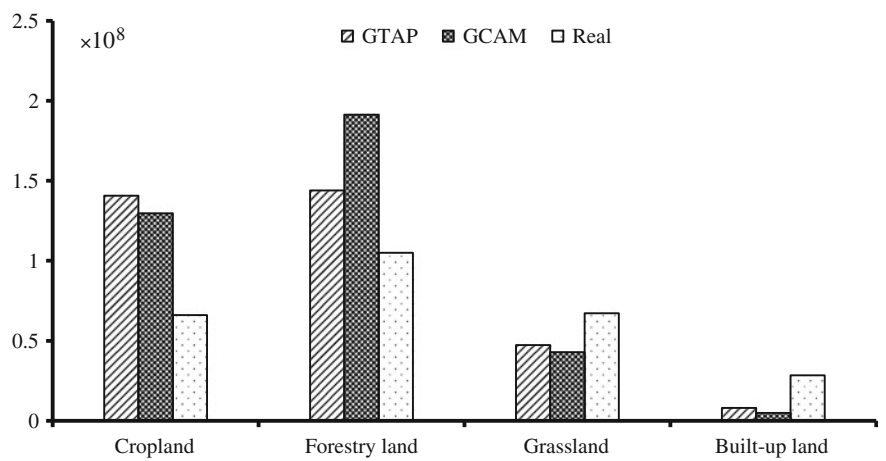


Fig. 2.6 The comparison of land use area between simulated and real in 2008 (hectare)

Table 2.3 The adjustment of GCAM input parameters (%) in 2010

Input parameters	Previous parameters	Adjusted parameters
GDP growth	10	10.4
Labor growth	0.4	0.4
Capital growth	12.6	12.8
TFP growth	0.9	1.1
Population growth rate	0.8	0.5

that the distribution of different land use types among AEZs is approximately consistent, but with some difference between them.

There is still some difference between the real land use area and that obtained with the two models, and the simulation result with the GTAP-AEZ model is better than that with the GCAM model (Fig. 2.6). The results show that the area of cropland and forestry land simulated with the GCAM model and the GCAM model are far higher than the real one, which is 2.13 and 1.96 times larger than the real one, respectively. However, the areas of grassland and built-up land simulated with the two models are both lower than real values. This indicates there is still some inaccuracy in data of the land use structure, industry structure, and social economic situation of China in the global simulation. For example, the forest land should be divided into economic forest lands and ecological forest lands, but not distinguished in this study, leading to the significant difference between the simulated and real areas for the forest land.

There is an extremely complex socioeconomic structure and land use structure in China, both of which have changed greatly due to the rapid economic

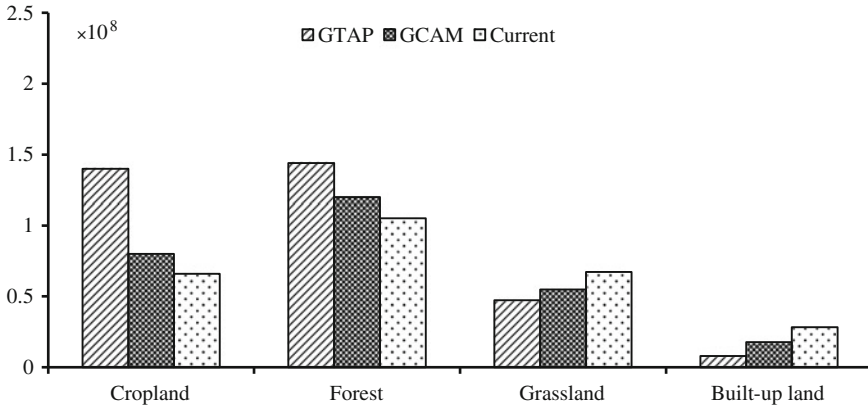


Fig. 2.7 The comparison of land use area in China in 2010 simulated with the calibrated GCAM model and the GTAP model and the real values (hectare)

development of China and consequently made it very difficult to accurately simulate the land use change in China using models with static data. For instance, the estate price in China has fluctuated prominently during the past decades, but a static estate price is first used in the GCAM model in this study, which makes it obviously difficult to simulate the constantly changing industrial structure in China. Therefore, it is necessary to calibrate the models before simulating the land use change.

In order to more accurately simulate the change of the land use structure in China according to the reality and improve the precision of future scenario simulation, we calibrated the parameters of the GCAM model and the GTAP-AEZ model (Table 2.3). The influence of policy intervention is included in the models according to the specific national condition of China, and other parameters were also calibrated. In this study, the price of agricultural products is set to increase by 1.5 % every year, TFP will increase by 0.1 %, and the annual population growth rate will decrease from 0.8 to 0.5 %. The results indicate that the land use structure simulated with the calibrated GCAM model becomes much more accurate than before and has more closely approached to the reality. Besides, the simulation accuracy with the calibrated GCAM model is much higher than that with the calibrated GTAP-AEZ model (Fig. 2.7).

2.3.5 Concluding Remarks on Combining Emission Scenarios with Land Use Changes

This study simulated the LUCC in China under the RCP 4.5 scenario with GCAM and GTAP-AEZ, and compared the simulated and real land use structures. The simulation results obtained with GCAM and GTAP-AEZ are generally consistent,

but also with some difference, and the land use structure simulated with GTAP-AEZ is more close to the real conditions in some AEZs than that obtained with GCAM. For example, the consistence between the forest land area simulated with GCAM and the real one reached more than 80 %, while that with GTAP-AEZ reached only 37 %. Overall, GCAM involves the driving factors of the rapid economic development, which makes the simulation more close to the reality. However, neither of the two models takes account of the impacts of policies on socioeconomic development, which also has great influence on the land use change. Therefore, it is necessary to calibrate the models through optimizing the model input parameters. When the models are calibrated through adjusting these socioeconomic parameters according to the specific conditions, the overall simulation accuracy of GCAM reached 82 % and that of GTAP-AEZ also reached 60 %. So that it is possible and necessary to improve the simulation accuracy through calibrating input parameters of the models according to the specific conditions.

In recent decades, more and more land use simulation models have been developed, but it is still a hard task to implement the calibration of input parameters for these models. In the study, the land use structure of China in 2010 is simulated with GCAM and GTAP-AEZ under the RCP 4.5 scenario, both of which were further calibrated through adjusting the input parameters, focusing on comparing the accuracy of the results simulated by two models. The result indicates the simulated areas of cropland and forest land with both two models are higher than the real one, while the simulated areas of grassland and built-up land were lower than the real values, and the accuracy is greatly improved after the calibration.

2.4 Summary

The framework of LUCD model compatible with RCMs was introduced, which has been divided into three sub-modules. The modeling approaches of three modules of the LUCD model should be accordant with specific RCM, so that we make the LUCC classification flexible in the LUCD model. However, due to the uncertainties of climate change, economic development, and other factors, it is very difficult to accurately simulate the long-term land use change in the future. Therefore, it is necessary to study more deeply on how to optimize the parameters according to the specific conditions in the future.

Finally, we introduced the Global Change Assessment Model (GCAM) and the GTAP-AEZ model which can take account of the influence of social economy and climate change at the global scale. We simulated the land use structure of China in 2010 with the two models and compared the results with the real one. Also, we calibrated these parameters of models according to the China's national conditions and implemented the simulation again. The result indicates that the calibrated

GCAM can provide more accurate result of land use, which can provide significant reference information for the land use planning and policy formulation to mitigate and adapt the climate change in China.

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