

## Chapter 2

# Impact Assessments on Agricultural Productivity of Land-Use Change

Jinyan Zhan, Feng Wu, Zhihui Li, Yingzhi Lin and Chenchen Shi

**Abstract** Currently, food safety and its related influencing factors in China are the hot research topics, and cultivated land conversion is one of the significant factors influencing food safety in China. In this chapter, we first investigated land degradation induced by land-use change. Land degradation is a complex process which involves both the natural ecosystem and the socioeconomic system, among which climate and land-use change are the two predominant driving factors. To comprehensively and quantitatively analyze the land degradation process, we employed the normalized difference vegetation index (NDVI) as a proxy to assess land degradation and further applied the binary panel logistic regression model to analyze the impacts of the driving factors on land degradation in the North China Plain. The results revealed that increasing in rainfall and temperature would significantly and positively contribute to the land improvement, and conversion from cultivated land to grassland and forest land showed positive relationship with land improvement, while conversion to built-up area will lead to land degradation. Besides, human agricultural intensification represented by fertilizer utilization will help to

---

J. Zhan (✉) · F. Wu · C. Shi

State Key Laboratory of Water Environment Simulation, School of Environment,  
Beijing Normal University, Beijing 100875, China  
e-mail: zhanjy@bnu.edu.cn

Z. Li

Institute of Geographic Sciences and Natural Resources Research,  
Chinese Academy of Sciences, Beijing 100101, China

Z. Li

Center for Chinese Agricultural Policy, Chinese Academy of Sciences,  
Beijing 100101, China

Z. Li

University of Chinese Academy of Sciences, Beijing 100049, China

Y. Lin

School of Mathematics and Physics, China University of Geosciences (Wuhan),  
Wuhan 430074, China

improve the land quality. The economic development may exert positive impacts on land quality to alleviate land degradation, although the rural economic development and agricultural production will exert negative impacts on the land and lead to land degradation. Infrastructure construction would modify the land surface and further resulted in land degradation. The findings of the research will provide scientific information for sustainable land management. Second, we predicted land-use conversions in the North China Plain based on the scenario analysis. Scenario analysis and dynamic prediction of land-use structure which involve many driving factors are helpful to investigate the mechanism of land-use change and even to optimize land-use allocation for sustainable development. In this study, land-use structure changes during 1988–2010 in North China Plain were discerned and the effects of various natural and socioeconomic driving factors on land-use structure changes were quantitatively analyzed based on an econometric model. The key drivers of land-use structure changes in the model are county-level net returns of land resource. In this research, we modified the net returns of each land-use type for three scenarios, including business as usual (BAU) scenario, rapid economic growth (REG) scenario, and coordinated environmental sustainability (CES) scenario. The simulation results showed that, under different scenarios, future land-use structures were different due to the competition among various land-use types. The land-use structure changes in North China Plain in the 40-year future will experience a transfer from cultivated land to built-up area, an increase of forestry land, and decrease of grassland. The results will provide some significant references for land-use management and planning in the study area. Third, we simulated shifting patterns of agroecological zones across China. An agroecological zone (AEZ) is a land resource mapping unit, defined in terms of climate, landform, and soils, and has a specific range of potentials and constraints for cropping (FAO 1996). The shifting patterns of AEZs in China driven by future climatic changes were assessed by applying the agroecological zoning methodology proposed by International Institute for Applied Systems Analysis (IIASA) and Food and Agriculture Organization of the United Nations (FAO) in this study. A data processing scheme was proposed to reduce systematic errors in projected climate data using observed data from meteorological stations. AEZs in China of each of the four periods: 2011–2020, 2021–2030, 2031–2040, and 2041–2050 were drawn. It is found that the future climate change will lead to significant local changes of AEZs in China and the overall pattern of AEZs in China is stable. The shifting patterns of AEZs will be characterized by northward expansion of humid AEZs to subhumid AEZs in south China, eastward expansion of arid AEZs to dry and moist semiarid AEZs in north China, and southward expansion of dry semiarid AEZs to arid AEZs in southwest China.

**Keywords** Land degradation • NDVI • Land-use conversion • Scenario • Land-use simulation • Agroecological zones • North China Plain

## **Land Degradation Induced by Climate and Land-Use Change in the North China Plain**

### ***Introduction***

Land degradation has become a critical issue worldwide, especially in the developing countries, which lead to great concerns about food security. To improve livelihoods of human beings and to keep sustainable development of human society, healthy land ecosystems are basically essential elements. However, the key services of good-quality land and their true values have been usually taken for granted and underestimated, leading to serious land degradation, which not only deteriorates the ecosystem services but also hinders regional sustainable development. Land degradation means a significant reduction of the productive capacity of land. It is an interactive process involving various casual factors, among which climate change, land-use/land-cover changes, and human dominated land management play a significant role (Bajocco et al. 2012). Land degradation involves two interlocking complex systems, the natural ecosystem and the human social system, and both changes in biophysical natural ecosystem and socioeconomic conditions will affect the land degradation process (MEA 2005). Natural forces affect land degradation through periodic stresses of extreme and persistent climatic events. Human activities also contribute to land degradation through deforestation, removal of natural vegetation and urban sprawl that lead to land-use/land-cover changes; unsustainable agricultural land-use management practices, such as use and abuse of fertilizer, pesticide and heavy machinery; and overgrazing, improper crop rotation, and poor irrigation practices (WMO 2005).

In comparison with other regions, land degradation afflicts China more seriously in terms of the extent, intensity, economic impacts, and affected population (Bai and Dent 2009). China accounts for 22 % of the world's population, but only 6.4 % of the global land area and 7.2 % of the global cultivated land area. Agricultural production is an important issue that always plagues the national economy and livelihood of citizens (Deng et al. 2008a). However, the rapid population growth and urbanization, unreasonable human utilization, and influence of natural factors have caused degradation of 5.392 million km<sup>2</sup> of land, which accounts for about 56.2 % of the total national area. Only 1.3 million km<sup>2</sup> of land is suitable for cultivation in China, which accounts for about 14 % of the total national land area. The land degradation has involved more than half of the total cultivated land area and further exerts more pressure on the economic benefits of agricultural production and food security. Besides, as the cultivated land degradation will directly affect the potential land productivity, more inputs such as fertilizer and irrigation water will be needed in order to get the same production as well as yield level, which will increase the production cost (Li et al. 2011). In addition, the structural change and pattern succession of the land system resulting from land conversions will undoubtedly lead to changes in the suitability and

quality of land and directly influence land productivity. Hence, sustainable productive land management is crucial for the country's long-term agricultural economy.

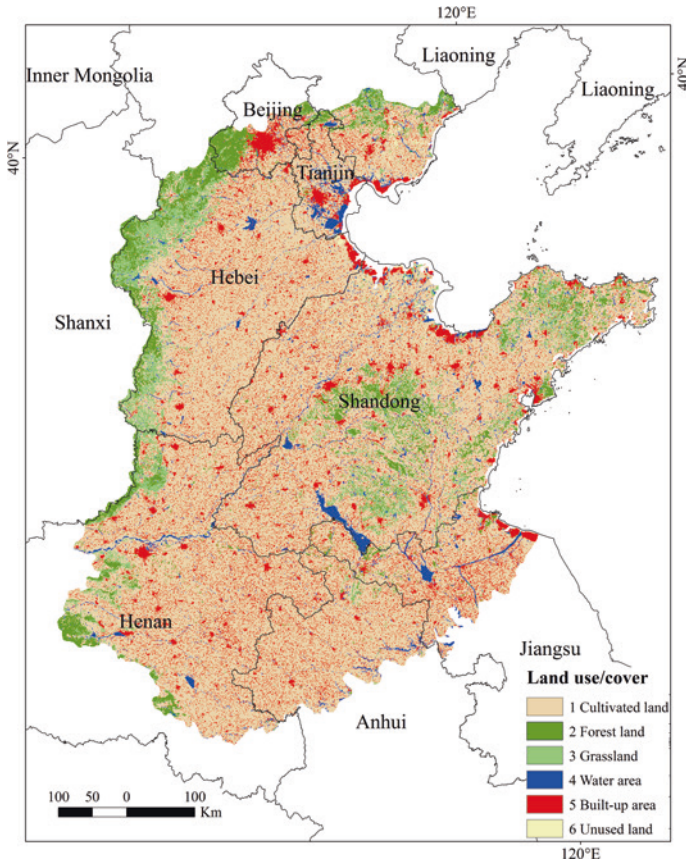
China is a large country with significant spatial variation of natural/climatic conditions and diverse socioeconomic characteristics. For example, the eastern, central, and western parts of China have different population density, industrial structure, and per capita income, etc. The difference among regions will affect the land use, leading to difference in the way and extent of economic use of land resources. The North China Plain has been one of the most productive agricultural bases in China for thousands of years. It is of great significance to quantitatively measure the intensity and spatial pattern of land degradation and analyze the driving mechanisms, which can provide information for sustainable land management to ensure the food safety in the North China Plain.

In order to provide information for sustainable land management, it is necessary to quantitatively clarify the impacts of major natural and socioeconomic driving forces on land degradation. The recent development of remote sensing techniques (RS) and geographic information system (GIS) techniques has enhanced the capabilities to obtain and handle spatial information on the heterogeneities of land surface characteristics. The integration of RS and GIS technologies has been proven to be an efficient approach and has been successfully used in various investigations for land degradation assessment. Land degradation is a long-term process indicating the loss of ecosystem function and productivity. For quantitative analysis of land degradation, satellite measurements of the normalized difference vegetation index (NDVI), which is the most widely used proxy for vegetation cover and production, has been widely applied in studies of land degradation from the field scale to national and global scales (Wessels et al. 2004; Bai and Dent 2009). Therefore, the objective of this study is to explore the spatial pattern and temporal variation of land degradation based on NDVI in the North China Plain, then to analyze the impact mechanisms of a set of natural and socioeconomic driving forces on land degradation, with the application of the binary panel logistic regression model.

## ***Data Processing and Analyses***

### **Land Uses in the North China Plain**

As estimated with the remote sensing data derived from the Landsat TM and ETM+ images in the year of 2008, the cultivated land accounts for about 68 % of the total land area of the North China Plain (Fig. 2.1). There is a semiarid to semihumid warm temperate climate in the North China Plain, with the average annual temperature of 10–15 °C, and annual rainfall of 500–800 mm. It is evident that the North China Plain is suitable for developing rain-fed agriculture and planting a variety of crops and fruit trees. Meanwhile, it is conducive to mechanization and irrigation with its natural conditions of a flat terrain, deep soil, and contiguous



**Fig. 2.1** Land-use pattern of the North China Plain in the year of 2008

land concentration. All of these unique conditions have made the North China Plain a major agricultural region and a significant commodity base for grain, cotton, meat, and oil in China.

However, the rapid population growth and urban land expansion have led to serious cultivated land loss and environmental degradation in the North China Plain. Many researches showed that the conversion from cultivated land to other types of land led to the decrease of cultivated land in the North China Plain (Jiang et al. 2011) pointed out that the area of cropland abandonment was much greater than the area of cropland reclamation in the North China Plain (Jiang et al. 2011; Shi et al. 2013). Besides, the quality of cultivated land converted to other land-use types is generally higher than that of the cultivated land converted from other land-use types. As a result, the shrinkage of cultivated land in the North China Plain will exert great impact on the land quality. How to improve land productivity is becoming vital for the improvement of agricultural production. In addition, though the statistic data showed that the grain yields were increasing, it is due to

the additional investment into the agricultural production. With this regard, it is an urgent issue to study how to make scientific policy and sustainable land management measures to rationally regulate the land conversion and control land degradation to improve the productivity of the remaining resources in the agricultural sector.

## Data Preparation

According to previous studies, driving factors of land degradation are complex. Among which, biophysical causes (include topography that determines soil erosion hazard, and climatic conditions, such as rainfall and temperature) and land-use change (such as deforestation, desertification resulted from unsustainable land management practices) are major direct contributors to land degradation, while the underlying causes of land degradation include population density, economic development, land tenure, and access to agricultural extension, infrastructure, etc. Thus, in order to analyze the situation of agricultural production and impact mechanisms of climate and land-use change integrated with socioeconomic factors on cultivated land degradation in the North China Plain, we collected the NDVI data, land-use datasets, climatic data, socioeconomic statistical data, and other geophysical data of the year of 2000–2008.

**NDVI.** NDVI is one of the most commonly used indicators for vegetation monitoring (Tucker 1979). Many previous studies have used the NDVI and other measures based on the NDVI as indicators of changes in ecosystem productivity and land degradation, which showed that NDVI is strongly correlated with the green vegetation coverage (Elhag and Walker 2009). Though there are some limitations and criticisms related to the use of this measure, NDVI remains the only dataset available at the global level and the only dataset that reliably provides information about the condition of the aboveground biomass (Nkonya et al. 2011). In this study, we used the remote sensing data of NDVI to measure the land degradation. Before 2006, the NDVI data were obtained from the GIMMS NDVI dataset produced by the GLCF (Global Land Cover Facility) research group at the University of Maryland from July 1981 to December 2006, with a spatial resolution of 8 km by 8 km and a temporal resolution of 15 days. The NDVI data after the year 2006 were derived from SPOT VEGETATION data (ten-day ensembles) which were derived from a dataset developed over the period from April 1998 to December 2010, with a spatial resolution of 1 km by 1 km. Based on the period when the two datasets overlapped (1998–2006), we conducted data processing according to the previous experience of Yin et al. (2014). Firstly, correlation analysis between the maximum monthly NDVI and other factors was performed, following which a linear regression equation was established to extend the Global Inventory Modeling and Mapping Studies (GIMMS) dataset from 2007 to 2008. This helps to eliminate any sensor error in the other two datasets. To ensure the data quality, reliable and internationally recognized data pretreatment processes were used. In order to eliminate cloud contamination effects and the noise caused by other atmospheric

phenomena, we included a smoothing method proposed by Chen et al. (2004) based on the Savitzky-Golay filter. Finally, we clipped the NDVI data of the North China Plain during the period from the year of 2000 to 2008.

*Land use.* The land-use data came from the land-use database of the Resources and Environment Scientific Data Center, Chinese Academy of Sciences (Liu et al. 2010). The database was constructed from remotely sensed digital images by the US Landsat TM/ETM satellite with a spatial resolution of 30 by 30 m. Further the land-use data are upscaled to 1 by 1 km. The data that were analyzed in this study covered the year of 2000 and 2008.

*Climatic data.* The climatic data, mainly including temperature and rainfall from the year of 2000 to 2008, were derived from the daily records of 117 observation stations covering the entire area of the North China Plain, which were maintained by the China Meteorological Administration. A spline interpolation using the coupling-fitted thin-plate interpolation method was chosen to interpolate the meteorological data. Based on the climatic dependence on topography, climatic variables were interpolated with spatial resolution of 1 by 1 km. At a broader scale, temperature declined roughly with the increasing elevation at a typical standard lapse rate of 6.5 °C per 1 km, so the interpolated air temperature data were adjusted to the sea level according to the altitudinal correction factors based on the digital elevation model (DEM) dataset.

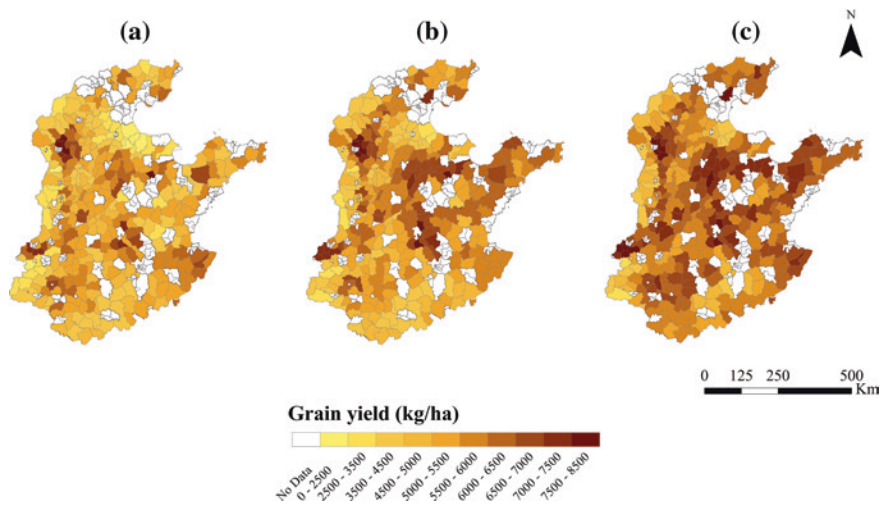
*Soil organic matter.* The soil fertility map of the study area was clipped from the soil map of China provided by the Institute of Soil Science, Chinese Academy of Sciences. It was based on the maps on the scale of 1:4,000,000 from the Second National Soil Survey of China for Soil Organic Matter (SOM).

*Socioeconomic statistical data.* In this study, we collected and processed the socioeconomic data of 385 major counties in the North China Plain at a county level for the period of the year of 2000–2008, including the gross domestic production (GDP), population, rural farmers' per capita income, fertilizer utilization, pesticide utilization, farm machinery, total grain production, and total grain sown area, which were all acquired from socioeconomic statistical yearbooks published by National Statistical Bureau of China.

*Geophysical data.* The geophysical data are also closely related with the land productivity. In this specific study, the geographic factors mainly include elevation and average slope, the data of which were derived from China's Digital Elevation Model Dataset supplied by the National Geomatics Center of China. Another part of the geophysical data was the proximity variables, including the distance from each grid to the nearest expressway or highway, and other way, which were incorporated to measure the impacts of the infrastructure construction on the land degradation.

## Primary Analysis

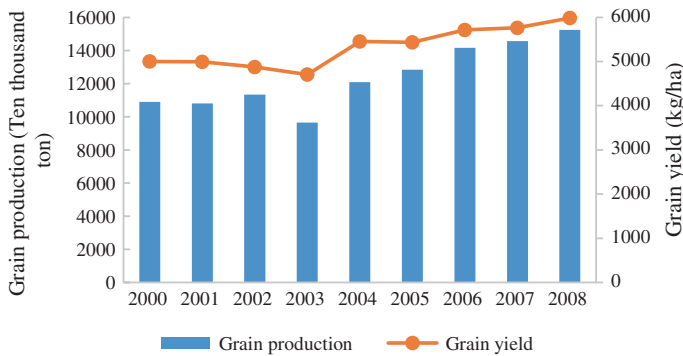
*Changes of grain production.* We analyzed the changes of grain production and the relationship between total grain production and grain yield (kg/ha) of the North China Plain during the year of 2000–2008. The spatial distribution of grain



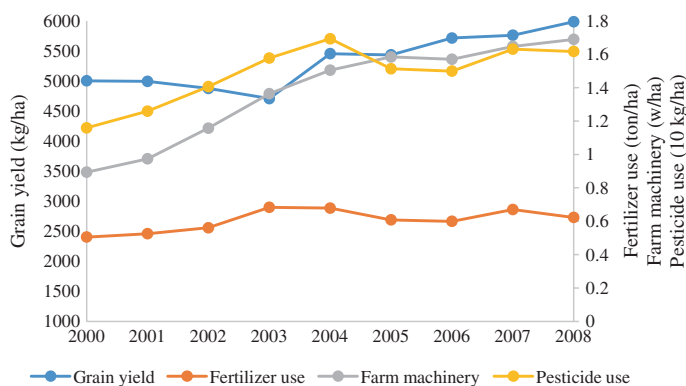
**Fig. 2.2** County-level grain yield of the North China Plain, **a** 2000, **b** 2005, and **c** 2008

yield at municipality or county level in the year of 2000, 2005, and 2008 is shown in Fig. 2.2. The grains mainly included wheat and maize, but some rice, soybean, and tuber crops were also included.

During the period of the year of 2000–2008, annual total grain production of the selected counties of the North China Plain increased by more than 40 %, and the average grain yield increased from 4994 to 5986 kg/ha (with an increasing rate of 20 %). The time-series changing trend of the total grain production is similar to that of the average grain yield, and therefore, the increase of agricultural production can be mainly ascribed to the increase in the average grain yield (Fig. 2.3). The time-series change of grain yield from the year of 2000 to 2008 can be divided into two periods. Firstly, the average grain yield decreased after



**Fig. 2.3** Relationship between grain production and grain yield of the North China Plain, 2000–2008

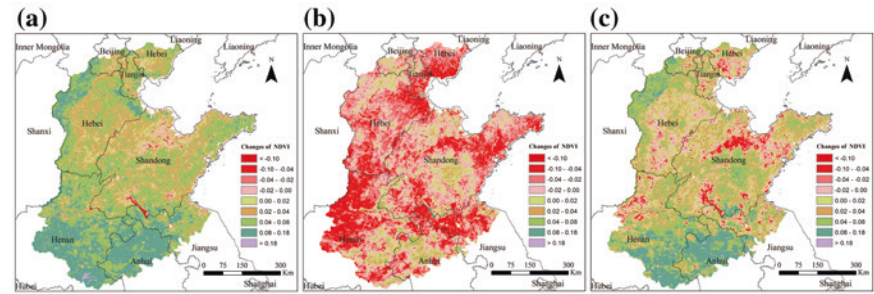


**Fig. 2.4** Changes of grain yield, fertilizer use, pesticide use, and farm machinery application of the North China Plain, 2000–2008

the year of 2000 because of a decrease in grain price. Secondly, the price of grain increased again through governmental support after the year of 2003, which made the average yields recover again.

Also, we showed that the application rates of fertilizer and pesticide increased with fluctuations from 525 to 622 kg/ha and from 12.6 to 16.2 kg/ha during the period of the year of 2000–2008, respectively. The application rate of the farm machinery also showed an increasing trend (Fig. 2.4). The increase of the application of farm machinery, fertilizer, and pesticide can be the key determinants of the increase in crop yield; however, further increases in fertilizer and pesticide application are unlikely to be as effective as they previously were in increasing the grain yields because of the gradually diminishing return rate.

*Trends in NDVI.* The annual average greenness (represented with NDVI) is chosen as the standard proxy of annual average biomass productivity, which generally fluctuates with the rainfall. The NDVI calculated using remote sensing image data, currently is one of the most commonly used indicators to monitor regional or global vegetation and the ecosystem, and is the best instruction factor to reflect vegetation growth conditions and coverage (Zhang et al. 2005). In this study, the cultivated land degradation areas were identified with a sequence of analyses of the NDVI data. The result shows that the annual average NDVI of the North China Plain showed an overall increasing trend during the year of 2001–2004. About 90 % of the study area's annual average NDVI experienced an increasing trend. While only 5 % of the study area's annual average NDVI showed a decreasing trend, which was distributed in the Shandong Province (Fig. 2.5a). In comparison, during the years 2004–2008, about 80 % of the study area's annual average NDVI experienced a decreasing trend, with only 19 % of the study area's annual average NDVI showed an increasing trend (Fig. 2.5b). Besides, the annual average NDVI in some areas showed first an increasing and then a decreasing trend during the year of 2000–2008. Overall, the annual average NDVI showed an increasing trend in most part of the whole study area during the year of 2000–2008 (Fig. 2.5c).



**Fig. 2.5** Changes of NDVI of the North China Plain during **a** 2000–2004; **b** 2004–2008, and **c** 2000–2008

*Land-use change.* During the year of 2000–2008, the land-use change is mainly dominated by the conversion from cultivated land to other land-use types, especially the conversion from cultivated land to built-up land. As cultivated land is the major land-use types in the study area, thus we focus on the cultivated land conversion. In the North China Plain, cultivated land is mainly converted to built-up land (67 %), forest land (9.1 %), and grassland (12.4 %) (Fig. 2.6).

**Associations Between Climate Factors and Land Degradation**

We investigated the relationship between NDVI (from the year of 2000 to 2008) and climate factors. The relationship between NDVI and climate indicators is widely analyzed in many previous studies, which have confirmed that vegetation changes are closely related to changes in the climate factors at the global or regional scale. In particular, it is widely acknowledged that the temperature and rainfall are the most significant factors influencing the ecosystem characteristics and distribution. We sampled the value of the NDVI, rainfall, and temperature and calculated their annual average values in the whole North China Plain. The mean NDVI, temperature, and rainfall for the study area were plotted along a nine-year time series (Fig. 2.7). Figure 2.7 visually shows that the average NDVI experienced a fluctuated increasing trend, and the average rainfall and temperature slightly showed an increasing trend with some fluctuations.

Specifically, to study the responses of NDVI to the climate change, we analyzed the spatial correlation of NDVI with rainfall and temperature using the correlation analysis at the pixel scale. Figure 2.8 shows the spatial distribution of the correlation of NDVI with rainfall and temperature, respectively. It shows that the rainfall has a strong effect on NDVI, and there was a positive correlation between rainfall and NDVI in most part of the study area, especially in the northern part of the study area where it showed a high correlation. As to the relationship between NDVI and temperature, there was generally a positive relationship between NDVI and temperature, only in the northern part of the study area showed negative relationships.

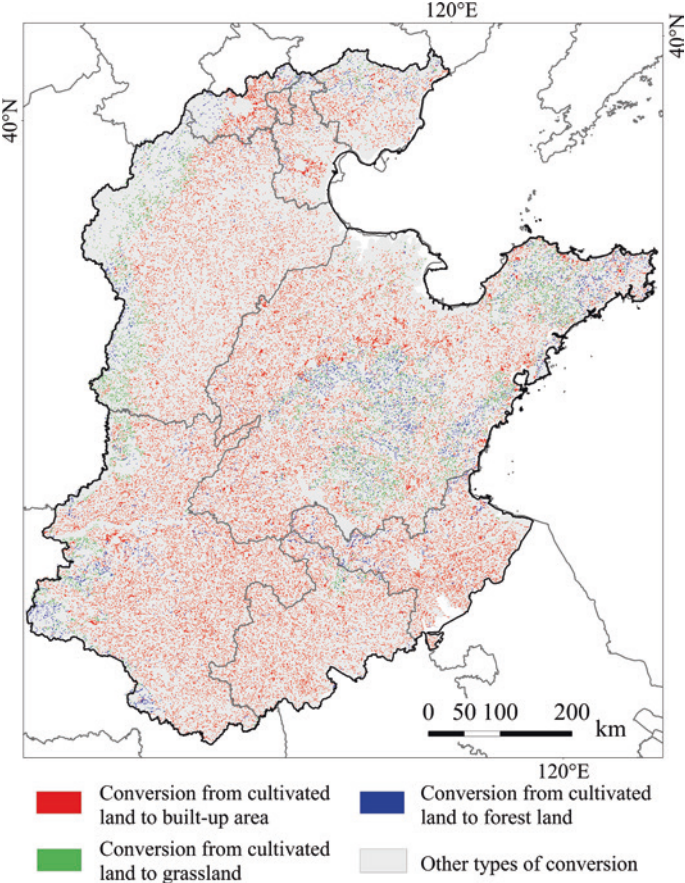


Fig. 2.6 Land conversion from cultivated land to three major land-use types during 2000–2008

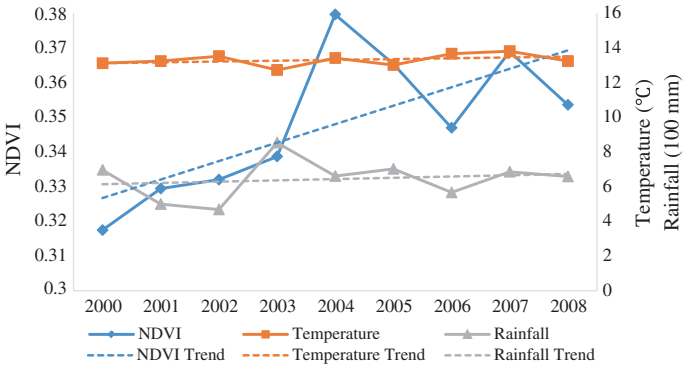
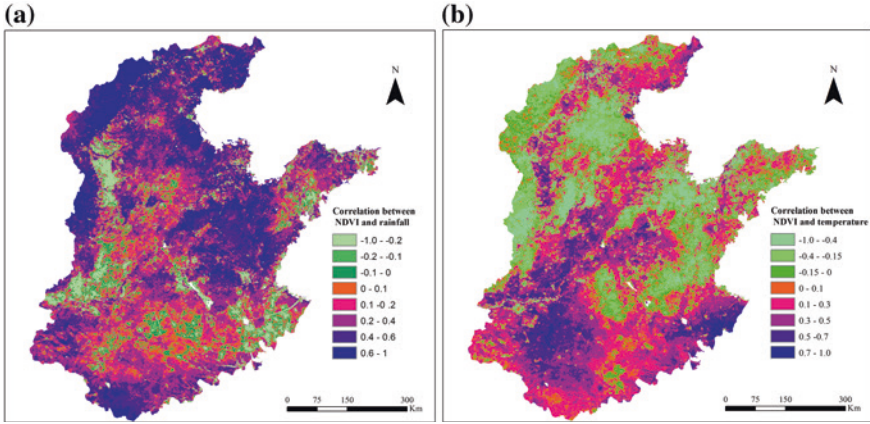


Fig. 2.7 Changing trend of spatially aggregated annual NDVI, rainfall, and temperature



**Fig. 2.8** Spatial patterns of correlation **a** between annual average NDVI and rainfall, and **b** between annual average NDVI and temperature at the pixel level in the North China Plain

### *Assessments of the Driving Forces of Land Degradation*

The causes of land degradation are numerous, interrelated, and complex. The relationship between direct and underlying causes of land degradation is complex also, and the impact of underlying factors is context specific (Nkonya et al. 2011). Quite often, the same cause may lead to diverging consequences in different contexts because of its varying interactions with other proximate and underlying causes of land degradation. This implies that targeting only one underlying factor is not sufficient in itself to address land degradation. It is necessary to take into account a number of underlying and proximate factors when designing policies to prevent or mitigate land degradation. For our model specification, it is essential to identify the effects of various combinations and interactions of underlying and proximate causes of land degradation in a robust manner rather than only analyze the individual cause of land degradation. With this regard, we try to identify the key underlying and proximate causes of land degradation. In this part, we conducted econometric analysis of the causes of land degradation in the North China Plain with the binary logistic regression model.

We constructed the model for estimating causes of land degradation or land improvement at the county level, using annualized data, and the model specification is as follows:

$$\text{Logistic } Y_t = \beta_0 + \beta_1 \Delta x_{1t} + \beta_2 \Delta x_{2t} + \beta_3 x_3 + \beta_4 x_4 + \varepsilon_{it}$$

$Y_t = 1$ , if  $\text{NDVI}_t - \text{NDVI}_{t-1} \geq 0$  and  $Y_t = 0$  if  $\text{NDVI}_t - \text{NDVI}_{t-1} < 0$ ;

$x_{1t}$  a vector of biophysical causes of land degradation (e.g., climate conditions, topography, soil fertility constraints);

- $x_{2t}$  a vector of demographic and socioeconomic causes of land degradation (e.g., population density, per capita GDP, rural farmers' per capita income, and agricultural intensification);
- $x_3$  a vector of variables representing access to infrastructure services (e.g., distance to expressway, distance to high way, and distance to other way);
- $x_4$  a vector of variables representing land-use change (e.g., county-level percentage of land conversion from cultivated land to built-up land, forest land, and grassland during the year of 2000–2008)

$Y_t$  is a binary variable that being used to identify whether land degradation happens, if  $Y_t$  equals or is larger than zero, then we assume that there happens land improvement; otherwise, there happens land degradation. Furthermore, we applied a binary panel logistic regression model to simultaneously study the relationship between land degradation conditions and all other variables. Table 2.1 illustrates the results of the regression. The results are to be interpreted with extreme caution due to the complex and multidirectional relationship between NDVI changes and the selected variables. Note that the results might not indicate a causal relationship but only an association between NDVI and the selected biophysical and socioeconomic variables (Nkonya et al. 2011).

**Table 2.1** Results for binary panel logistic regression analyses for the biophysical and socioeconomic driving forces of land degradation

| Land degradation conditions $Y$ (1 represents land improvement and 0 represents land degradation) | Coef.    |
|---------------------------------------------------------------------------------------------------|----------|
| $\Delta$ Rainfall (mm)                                                                            | 3.221*** |
| $\Delta$ Temperature ( $^{\circ}\text{C}$ )                                                       | 1.025*** |
| Percentage of land conversion from cultivated land to built-up land (%)                           | −0.326   |
| Percentage of land conversion from cultivated land to forest land (%)                             | 1.788    |
| Percentage of land conversion from cultivated land to grassland (%)                               | 8.507*   |
| $\Delta$ Fertilizer utilization per unit area (kg/ha)                                             | 0.506**  |
| $\Delta$ Population density (ten thousand people/km <sup>2</sup> )                                | −11.282  |
| $\Delta$ Rural farmers' per capita income (ten thousand yuan)                                     | −0.076   |
| $\Delta$ Per capita gross domestic production (ten thousand yuan)                                 | 0.0004   |
| $\Delta$ Share of production value of agriculture, animal husbandry, and fishery in GDP (%)       | −1.672*  |
| DEM (km)                                                                                          | 3.214    |
| Slope (degree)                                                                                    | −0.018   |
| Soil organic matter (%)                                                                           | 0.446*** |
| Distance to highway (km)                                                                          | 0.002*   |
| _cons                                                                                             | 0.032    |

Note \*Significant at the 10 % level

\*\*Significant at the 5 % level

\*\*\*Significant at the 1 % level

Climate change is significantly related with the land degradation conditions which represented by the changes in NDVI. As expected, increments in temperature and rainfall are positively related with the increases in NDVI, and increases in temperature and rainfall will significantly contribute to land improvement. Land-use change is also the major driving force of land degradation. The results showed that the conversion from cultivated land to grassland and forest land will contribute to land improvement, which corresponded to increase in NDVI, while the conversion from cultivated land to built-up land would lead to land degradation. Among the land conversions, only the conversion from cultivated land to grassland significantly affects the land degradation. In comparison, climate change plays a much more important role than land-use change in land degradation. Besides, agricultural intensification represented by fertilizer utilization is significantly and positively related with land improvement, as fertilizer application increases soil carbon (Vlek et al. 2004), which could correspond to an increase in NDVI. Increases in the population density would lead to land degradation, but not significantly. According to the previous studies, the impact of population density on land degradation is ambiguous, while our results suggested that there would be more serious land degradation in areas with higher population density. The population growth will lead to increasing demand for housing and other facilities, which in turn can lead to increase of impervious surface as a result of urban development and infrastructure construction and deforestation. Rapid economic development, which can be represented by changes in the per capita GDP, shows that an increase in both GDP and NDVI had positive impacts on land quality, suggesting the role of ecosystem service could play in economic growth and prosperity. Economic development would stimulate the land improvement, but such impacts were not significant, while the rural economic development, represented by rural farmers' per capita income, showed negative relationship with land improvement, suggesting that the NDVI will decrease as the rural farmer's income increases. It may be due to the fact that rural economic growth develops at the cost of intensive land-use practice, which contributes to environmental degradation further lead to the land degradation. In addition, the increases in the share of the primary industry (agriculture, animal husbandry, and fishery) in GDP significantly corresponded to the decrease in NDVI, as production value of the agriculture increases were mostly resulted from the investment into agricultural production, such as fertilizer, pesticide, and farm machinery, not from natural land-quality improvement. In addition, the geographic and topographic factors also affect the land degradation. As to the topographic factors, the results showed that the higher the elevation and the slower slope, the less serious land degradation. The impacts of elevation was not significant, while it may suggest that in the areas with higher elevation, there would be less impact of anthropogenic factors on the land degradation. The slope had clear significant impacts on land degradation, suggesting steep slopes would lead to land degradation more easily, as steep slope region was more vulnerable to severe water-induced soil erosion. As to the soil fertility represented by SOM, the results showed that the higher the soil fertility was, the less possibility of land degradation. Besides, the distance to highway was significantly positively related

with land improvement, which suggested that the larger distances to road network meant there was less human disturbance, less infrastructure development and land-use change, which would exert less impact on the land degradation.

## *Summary*

Land degradation or improvement is an outcome of many highly interlinked direct and underlying causes, including natural, socioeconomic, and related agricultural practices. In China, many types of land degradation are occurring, such as grassland degradation, deforestation, and cultivated land degradation. In this study, we conducted an empirical study in the North China Plain and analyzed the basic grain production changes, the changing trend of NDVI, and the spatial pattern of relationship between climatic factors and NDVI. Further taking NDVI as a proxy for land degradation and improvement, we applied an econometric model to analyze the causes of land degradation.

According to the analyses, both the grain production and grain yield of the North China Plain showed an increasing trend during the year of 2000–2008; however, estimation based on the remotely sensed NDVI data showed that the North China Plain still experienced land degradation. Degraded areas have been expending in the northern part of the study area, though many parts of the study area showed land improvement. Based on the correlation analysis, the increases in temperature and rainfall corresponded to the increase in NDVI in most parts of the North China Plain, though some parts of the study area showed negative correlation between NDVI and temperature and rainfall. Further, according to the binary panel logistic regression analysis, the results showed there were strong impacts of some key biophysical and socioeconomic variables on land degradation. Some of these relationships were consistent with conclusions in previous case studies, while other showed complex differences. The results for climate factors were not surprising; increase in temperature and rainfall would contribute to land improvement. Different land-use changes exert different impacts on land degradation. Unsurprisingly, increasing of forest land and grassland would benefit land quality, while urban expansion would lead to land degradation. Our estimation results about the positive effects of agricultural intensification represented by fertilizer utilization on land degradation were also as expected, and the SOM was also a crucial positive factor for land-quality conservation. Rural economic and agricultural development may lead to land degradation. The rural economic and agricultural production growth exerted negative impacts on land quality, which means the development of rural economy and agricultural production led to land degradation. The increases in rural farmers' per capita income and primary production value ratio did not result in the improvement of land quality, which may be due to the overexploitation of land with insufficient investment into the land conservation. With this regard, an effective response to land degradation needs increasing incentives of farmers to conserve their cultivated land and improve their access to the knowledge and inputs that are required

for proper conservation. Promotion of such land improvements should be a development policy priority. During the process to promote rural economic development, the governments should also focus on the monitoring and assessment of land quality and make measures to improve land quality, and such improvement measures should be designed together with farmers to meet their prior needs and use appropriate techniques according to the local economic and social conditions. In addition, increasing accessibility to infrastructures may also have negative effects on land quality. Infrastructure development is the basis for regional prosperity, and a booming economy will result in more construction of infrastructure. The expansion of basic infrastructure of transportation such as roads, railways, and airports can further take up land resources and further result in land overexploitation and degradation. The covering of the soil surface with impervious materials as a result of urban development and infrastructure construction is known as soil sealing. Sealing of the soil and land consumption are closely interrelated, when natural, seminatural and cultivated land is covered by impervious surfaces and structures; this will degrade soil functions or cause their loss. To reduce the impacts of infrastructure construction on land quality, the local government should take the assessment of land degradation into consideration during the construction of infrastructures.

Based on the results of the above analysis, to achieve sustainable land management, climate change should be monitored so as to make adaptation measures to mitigate the impacts of climate change on land quality; along with the socioeconomic development, investments and better land management for improving land quality should be definitely encouraged through appropriate policy measures; human activities that change the land surface, such as infrastructure constructions, should be regulated on the basis of the assessment of impacts on land quality, and corresponding land conservation measures should be taken during the construction process.

## **Predicted Land-Use Conversions in the North China Plain**

### ***Introduction***

Land-use change, as the direct cause and response of regional environment change, has always been one of the core topics of global change research (Foley et al. 2005). It is difficult to analyze the relationship between land-use and climate change clearly. On the one hand, climate change should exert impacts on the production of cultivated land, forestry, grassland, and so forth. For example, agricultural yields can be directly affected by climate change through changing temperature and precipitation, the distribution of pests, and the frequency of forest fires, and the markets can also be affected by climate change (Haim et al. 2011). Moreover, in recent years, there have been a number of literature-analyzed effects of climate change on agricultural production, with the help of some models (Schlenker et al. 2005; Jiang et al. 2012b). From these pieces of literature, we can learn that hedonic price models are widely used to estimate the relationship

between county-level farmland values and climate variables such as temperature and precipitation. These models are then used to simulate the effects of climate change on the value of agricultural production (Deschenes and Greenstone 2007). Even so, some researchers think that it is unreasonable to use mean temperature in the analysis of climate change impacts on agriculture (Schlenker and Roberts 2009). They find that the grain output has a good positive correlation with temperature but then falls quickly as temperature increases above a certain threshold. Other studies support these findings for global timber productivity (Sohngen et al. 2001; Perez-Garcia et al. 2002). In most regions, crops are sensitive to climate change (Izaurrealde et al. 2003; Lobell and Field 2008). Usually, global warming will accelerate the crop development, alter the growing season, and enhance the maintenance respiration (Qu et al. 2013), while, as to animal husbandry development, global warming would lead to grassland degradation, which would reduce the amount of livestock grazing and then decrease the output of livestock production. Meanwhile, livestock grazing might promote the CO<sub>2</sub> emissions (Herrero et al. 2009). According to the researches mentioned above, climate change will affect the agriculture, forestry, animal husbandry production, and so forth; then, the demand for products of different land-use types can result in new balance of the supply of and demand for land and further lead to land-use structure changes. On the other hand, most of experts think that the climate system should take account of land use; that is, land-use/land-cover change plays an important role in climate change; for example, afforestation and reforestation can reduce atmospheric CO<sub>2</sub> concentrations, thus, to mitigate the emission of greenhouse gas, and deforestation can result in temperature rising and precipitation decreasing in some regions (Nobre et al. 1991). Then, through the connection of climate change, we can figure out that the land-use structure has relationships with climate change.

Research on land-use structure changes needs to identify the driving factors from a systemic perspective and choose an appropriate model as a tool to reflect the changes to spatial distribution on a certain scale (Deng et al. 2008b). At present, there have been some achievements in applying economic models and empirical statistical methods for analyzing the driving forces of the land-use structure changes, and the simulation about land structure change has a tendency of regionalization and of being microcosmic, while there is much more room for improvement in many links of such simulation researches (Deng et al. 2012). For example, quite a lot of case studies just simulated the changes of one or several types of land use and seldom comprehensively simulated macroscopic structural changes of all land-use types from a systemic perspective (Capozza and Helsley 1989). The change of land-use structure is a dynamic process, which should be based on regional socioeconomic development characteristics, cultural traditions, natural conditions, the previous trend of land-use structure changes, and other factors to acquire valuable simulation results for decision. And it is helpful to make the forecast and evaluation results more science oriented and rational by simulating regional land-use structure changes under different scenarios.

The North China Plain is located in 32–40°30'N, 113–120°30'E, which belongs to the warm temperate zone, with the flat terrain, deep soil layer, and peaks and

valleys of rainfall and heat in the same period. It covers seven provinces and cities, including Hebei, Henan, Shandong, Jiangsu, Anhui, Beijing, and Tianjin (containing 387 counties), and has an area of 33.4 million ha, among which the area of land is 21 million ha, and it is the largest plain in China. The region with convenient transportation developed industries, and sufficient labor is one of the most important agricultural regions, and its agricultural production has a great potential for development. The North China Plain is a region that was earlier developed and was greatly influenced by human activities, and it is also one of the economically developed regions in China. The distribution of towns and cities is relatively intensive in the North China Plain; in addition to Beijing and Tianjin, there are also more than 20 cities with a population of more than one million. In the North China Plain, the grain output accounts for 18.4 % of total national output; the output of cotton accounts for 40 % of total national output; and the output of oil-bearing crops also accounts for a large proportion in China.

In 2006, the GDP per capita (GDPPC) in the North China Plain reached 19,224.27 Yuan. According to the experience of industrialization and urbanization in the developed countries and districts, the urbanization development of the North China Plain has entered into the period of cluster development and the later period of industrialization development. Since the North China Plain is located in a vast plain area and the land-use types are relatively unitary, the core problem of land use lies in the contradiction between the cultivated land protection and nonagricultural construction land (Deng et al. 2008b). The North China Plain is one of the important commodity grain bases in China, while its built-up area's expansion has taken up a large amount of high-quality cultivated land resources, which poses threat to regional and national food security and ecological environment.

In the North China Plain, most researches focused on the impact of climate change on cultivated land. There are few researches of the response mechanism on grassland and built-up area, and only a few studies have explored the combined effects of climate change on the agricultural and forestry sectors. The North China Plain is China's traditional and important agricultural production base, and it is also a region where the population grows rapidly; economy and urbanization develop rapidly with obvious land-use conversion, especially the transfer between cultivated land and nonagricultural land use (Jiang et al. 2012a). Therefore, in this study, we selected the North China Plain as case study area to analyze the future land-use structure changes under different scenarios. And based on an econometric model, we analyzed the effect of natural conditions (climate factors such as precipitation, temperature, etc.) and socioeconomic factors on land-use structure changes. This study can provide reference for the decision making of the local land-use planning, urbanization management, and land-use management.

### ***Land-Use Change in the North China Plain***

In this study, the information about land-use structure and its changes was derived from the remote sensing images of the North China Plain in years 1988,

**Table 2.2** Land-use structure of the North China Plain in various years (*unit* ten thousand hectares)

| Land-use type   | 1988    | 1995    | 2000    | 2005    | 2010    | Change rate during 1988–2010 (%) |
|-----------------|---------|---------|---------|---------|---------|----------------------------------|
| Cultivated land | 2448.81 | 2410.86 | 2402.01 | 2372.28 | 2346.51 | −4.18                            |
| Forestry        | 467.01  | 472.01  | 470.82  | 471.05  | 471.48  | 0.96                             |
| Grassland       | 375.12  | 363.34  | 363.48  | 356.25  | 355.51  | −5.23                            |
| Water area      | 310.09  | 312.74  | 315.28  | 317.84  | 321.02  | 3.53                             |
| Built-up area   | 1137.88 | 1187.64 | 1197.93 | 1237.09 | 1263.32 | 11.02                            |
| Unused land     | 40.20   | 32.50   | 29.58   | 24.59   | 21.25   | −47.12                           |

\*Change rate during (*R*) 1988–2010 is calculated based on the following formula:  $R = (B - A)/A \times 100\%$ ; A represents the area of each type of land in 1988 and B represents the area of each type of land in 2010

1955, 2000, 2005, and 2010 though the man–computer interactive interpretation (Table 2.2). And the information can be used as the basic data for analyzing the driving mechanism of land-use structure changes.

According to the statistics in Table 2.2, in the North China Plain, cultivated land accounts for the largest share about 50 %, and built-up area, forestry, water area, and grassland overall occupy a certain proportion, which guaranteed the development of local farming, forestry, animal husbandry, side-line production, and fishery. From 1988 to 2010, there had been some changes in the macrostructure of land use; cultivated land and grassland decreased by 4.18 and 5.23 %, respectively. And along with the development of economy and expansion of urbanization, the built-up area increased by 11.02 % from 1988 to 2010. In addition, the change trends of each land-use type during 1988–2010 are also not the same; cultivated and unused land always showed a trend of decrease, while water area and built-up area showed a continual trend of increase. The forestry overall increased with interval decrease from 1995 to 2000, and the grassland overall decreased with a slight interval increase from 1995 to 2000.

## ***Data and Methodology***

### **Data**

The data used in this study include the basic geographic information data, socio-economic data, and climate data that can affect land-use structure changes. The basic geographic information data mainly include remote sensing data and biological geographic elements data. And the land-use data and climate information are uniformly rasterized into 1 km × 1 km grid cell. The land-use data mainly come from remote sensing images interpretation during 1988–2010 (Yin et al. 2010), and then, the information of interpreted raster data can be extracted from

**Table 2.3** Descriptive statistics of main variables at county level

| Variable                                            | Obs  | Mean       | Std. Dev.  | Min    | Max       |
|-----------------------------------------------------|------|------------|------------|--------|-----------|
| Population                                          | 1633 | 614,909.90 | 421,749.10 | 63,245 | 6,600,841 |
| Annual per capita income (Yuan)                     | 1366 | 1959.64    | 2414.40    | 823    | 46,739    |
| Total grain output ( <i>T</i> )                     | 1392 | 294,692.9  | 207,261.60 | 0      | 2,231,531 |
| Price index of agricultural products                | 1935 | 104.12     | 3.30       | 101.30 | 108.40    |
| Price index of forestry products                    | 1935 | 105.20     | 1.98       | 102.30 | 108.50    |
| Price index of animal husbandry products            | 1935 | 111.62     | 7.92       | 100.50 | 123.90    |
| NPP(net primary productivity) (gc/m <sup>2</sup> y) | 1933 | 352.66     | 85.39      | 143.74 | 827.50    |
| Annual average precipitation (mm)                   | 1930 | 688.14     | 208.84     | 257.44 | 1562.09   |
| Annual average temperature (°C)                     | 1930 | 13.57      | 1.46       | 3.23   | 16.28     |
| Land quality (dummy variable)                       | 1915 | 499.58     | 142.50     | 54.00  | 868.07    |

\*The observations are different because of the data availability in several counties (387 counties × 5 periods)

county level. And thus, we derived the geographic elements information of each county, including temperature and precipitation. The concrete operations of data are mainly based on ArcGIS 9.3 and STATA 10.0 platform, and the data eventually were prepared in the form of panel data for analyses (Deng et al. 2012).

In this study, the socioeconomic data and climate data of 378 counties in the North China Plain were collected in 1988, 1995, 2000, 2005, and 2010 (Table 2.3). However, the land-use data are of spatial data type. To make the land-use data match with the statistic data of socioeconomic factors, the land-use data should be aggregated into county level. And in order to increase the sample space, improve the degree of freedom, provide individual information, and make the estimated results more accurate, the data mentioned above were prepared into the format of panel data which integrated the cross-sectional data and the time-series data.

## Scenarios

In this study, the basic settings of parameters for future scenarios are as follows: the average annual growth rate of annual per capita income is 7 %; the population in China should increase to 1.36, 1.45, and 1.5 billion in 2010, 2020, and 2050, respectively. The data are derived from the forecast of National Planning and Chinese Academy of Social Sciences.

In this research, through investigating the rule of macroscopic land-use structure changes during the past 20 years in the North China Plain, three scenarios were designed, namely business as usual scenario (BAU), rapid economic growth scenario (REG), and coordinated environmental sustainability scenario (CES). The land-use structure changes of the North China Plain during 2010–2050 are simulated under the three different scenarios. These scenarios are story lines that

**Table 2.4** Regional trends in population and annual per capita income in the North China Plain assumed for the BAU, REG, and CES scenarios

| Scenario                 | Year                     |        |        |        |        |
|--------------------------|--------------------------|--------|--------|--------|--------|
|                          | 2010                     | 2020   | 2030   | 2040   | 2050   |
| Population               | (Hundred million people) |        |        |        |        |
| BAU                      | 2.48                     | 2.51   | 2.54   | 2.57   | 2.6    |
| REG                      | 2.54                     | 2.69   | 2.64   | 2.63   | 2.64   |
| CES                      | 2.42                     | 2.52   | 2.45   | 2.35   | 2.33   |
| Annual per capita income | (Yuan)                   |        |        |        |        |
| BAU                      | 3375.6                   | 4537.8 | 5873.6 | 6974.3 | 7825.4 |
| REG                      | 3407.9                   | 4769.8 | 6200.7 | 7443.3 | 8930.7 |
| CES                      | 3442.4                   | 4625.4 | 5921.4 | 7220.5 | 8378.5 |

*Note* The annual per capita income was calculated and adjusted based on the consumer-price index of year 2000 to eliminate the effect of inflation

represent different future developments regarding population growth, economic growth, and environmental sustainability (Table 2.4). We adopted the population and income assumptions of the three scenarios to develop associated projections of built-up area returns. We modified agricultural returns with projections of agricultural prices produced for each of these scenarios. Finally, we incorporated agricultural and forest yield changes into the scenarios. From 2010 to 2050, population and annual per capita income increase gradually and the population growth rate in the REG is the highest and about 1.3 % higher than that in the CES scenarios. The REG scenario has higher annual per capita income, which is 24 % higher than that in the CES scenario in 2050.

BAU scenario was designed according to the socioeconomic conditions and the local development plan of the North China Plain, which can comprehensively and objectively reflect real conditions of local production activities and economic development.

REG scenario and CES scenario were designed with different conditions of economic development and ecological environmental sustainability to simulate the land-use structure changes at county level. This study intends to simulate the land-use structure changes, respectively, under different scenarios, among which the REG scenario is giving priority to economic development and the CES scenario is giving priority to ecological environmental sustainability and further provides reference for regional-level land-use exploitation, planning, and management.

Most agricultural commodities are traded internationally. And, therefore, it makes sense to focus on how climate change will affect global agricultural prices; thus, this study applied the basic linked system (BLS), a computable general equilibrium model that represents all of the major economic sectors, including agriculture, together with the agroecological zone (AEZ) model, which can assess the effects of climate change on agricultural systems to analyze the impact of climate change. The regional price indexes of all crops in the three scenarios are shown in Table 2.4. From the national point of view, the area of cultivated land will decrease

**Table 2.5** National agricultural price indexes under the BAU, REG, and CES scenarios

| Scenario | Year |       |       |       |       |       |
|----------|------|-------|-------|-------|-------|-------|
|          | 2000 | 2010  | 2020  | 2030  | 2040  | 2050  |
| BAU      | 100  | 108   | 136.5 | 180.7 | 228.4 | 250.8 |
| REG      | 100  | 109.7 | 147.4 | 188.7 | 230.1 | 267   |
| CES      | 100  | 108.6 | 149   | 190.6 | 237.2 | 274.6 |

year by year, the future mode of agricultural production will gradually transfer from cultivated land to grassland, and increase of built-up area will not bring small impact on cultivated land, so the national and regional agricultural price index is rising constantly in the future (Table 2.5). The national agricultural price index has obvious rising trend year by year, and it is significantly higher under the REG and CES scenarios than that under the BAU scenario, which means that in order to guarantee the REG and the sustainable development of ecological environment, it will inevitably lead to the changes of land-use structure and further affect the changes of industrial structure and product price.

**Methods**

As to the methods used to project land-use structure under the BAU, REG, and CES scenarios, in the first subsection, we discuss the land-use simulation model. The key driver of land-use structure changes in the projection model is county-level net profits of cultivated land, grassland, forestry, and built-up area. These variables are modified in the three scenarios according to assumed changes in population and annual per capita income and to predicted changes in regional agricultural prices, NPP, and forest carbon. And in the subsequent subsections, we discuss how these projections are scaled down to the county level and linked to the net profits.

**Land-Use Simulation Model**

In this study, based on the econometric model that Haim et al. (2011) used to study the relationship between climate change and future land-use change in USA, the land-use simulation model is developed through adjusting the variables that affect the net profit of each land-use type. In the model, the change of the overall land system with various land-use types can be simulated, and it allows transfers of different land-use types. This study applied the historical data of the North China Plain to estimate the land owners’ response to economic benefits and further make decisions on land-use allocation. The county-level net profits of cultivated land, forestry, grassland, and built-up area are regarded as the main driving factors of land-use structure changes, and the net profits are calculated synthetically based on population, annual per capita income, agricultural prices, NPP, and so forth. Climate change can indirectly affect the net profits through causing the change of

some factors, and according to the principle of maximum benefits, it will affect land-use allocation.

In this model, the area of each land-use type is the dependent variable, and the net profit and quality of each land-use type are independent variables. The net profit variables provide the link between different land-use types, which can be described in detail as follows.

The general equation for the net profit in county  $c$  is as

$$NP_{mc} = \sum_m \omega_{mc} p_{mc} q_{mc} - \sum_m \omega_{mc} c_{mc} \quad (2.1)$$

where  $\omega_{mc}$  is the net profits for commodity type  $m$  in county  $c$ ,  $p_{mc}$  is the per unit price for commodity type  $m$  in county  $c$ ,  $q_{mc}$  is the per acre average yield of commodity type  $m$  in county  $c$ , and  $c_{mc}$  is the per hectare cost of producing commodity type  $m$  in county  $c$ . Thus, the net profits of different land-use types can be calculated as the income of all the products minus the cost.

In the model, it is assumed that the land owners' expected values of the net profits of land are fixed, and they would change the land-use type in order to get the maximum net profits. The net profits include deterministic and stochastic components; the deterministic components include county-level net profits, land quality, and interaction between the two variables, and the stochastic components are estimated through the nested logistic model according to the distribution hypothesis (Jiang et al. 2012a). In this study, four main types of land use are taken into consideration, which are cultivated land, forestry, grassland, and built-up area. The probabilities of the transfer of different types of land use can be calculated based on the econometric model shown in (2.2), in which the independent variables and estimated parameters are incorporated to calculate the probabilities:

$$P_{ijk}^t = P(\varepsilon_{jk}, NP_i^t, LQ_i) \quad (2.2)$$

where  $P_{ijk}^t$  is the probabilities that the land-use type  $j$  be transferred to land-use type  $k$  in region  $i$  during the research period,  $\varepsilon_{jk}$  is the vector of estimated parameters,  $LQ_i$  is the dummy variable that indicates land quality of region  $i$ .

Scenario simulations are performed at county level, taking year 1988 as the baseline, and for simplicity, years 1988, 1995, 2000, 2005, and 2010 are noted as  $t = 0, 1, 2, 3, 4$ ,

$$S_{ijk}^{t+1} = \sum_k P_{ijk}^t \cdot S_{ikt} \quad (2.3)$$

where  $S_{ijk}^t$  is the area of land-use type  $j$  in region  $i$  at time  $t$ , and we can get the sequence of transfer probabilities with Eq. (2.2), and then future land-use allocation can be calculated. The land-use structure changes from time  $t$  to time  $t + 1$  indicates the change of supply of land products and services and further indicates the change of net profits and prices of all land-use types. In this study, the prices of land products of cultivated land, forestry, grassland, and built-up land are regarded as exogenous variables.

As the area of each type of land use ( $S_{ij0}$ ) in baseline year was known, the land-use structure changes till 2050 can be simulated based on the Eq. (2.3). The transfer probability  $P_{ikj}^t$  can be derived from Eq. (2.2), and  $P_{ikj}^t$  is a function of county-level net profit. Thus, once we get the county-level net profit, the future land-use structure changes can be simulated.

### Estimation of Net Profits

**Net Profit of Built-Up Area.** According to the standard urban land rent theory, population and income growth are the two main determinants of the value of urban land (Capozza and Helsley 1989). Based on the statistical model using county-level panel data, the net profit of built-up area as the dependent variable can be linked with the population and income as independent variables at county level. And according to the theory, population and annual per capita income are positively correlated with the built-up area value. High annual per capita income increases the demand for housing, and high population growth increases the price of habitable land. So, we can choose population and annual per capita income as two indicators to simulate and predicate the future net profit of built-up area.

**Net Profit of Cultivated Land.** According to (2.1), using the price index of agricultural products released by National Bureau of Statistics, the net profit of cultivated land can be calculated. Considering the condition of marked economy in China, it is reasonable to apply the nation price index to county-level estimation, and it is the same to the county-level price index of forestry products and animal husbandry products.

**Net Profits of Forestry and Grassland.** Based on the MAPSS model, it was assumed that the changes of forestry products and animal husbandry products were positively correlated with NPP. Through optimal management measures, the NPP of forestry and grassland can reach the maximum value. And the NPP was calculated based on the leaf area index (LAI) and NDVI.

### Validation of the Model

In order to validate the accuracy of the model, that is, to verify whether the simulation results can meet with the actual situation of land use, based on the historic data of land use, we do the validation as follows. Based on the model and actual land-use data in 2005, we simulate the land-use structure in 2010, then calculate the deviance between the actual land-use structure in 2010 and the simulated land-use structure, and thus measure the accuracy of the model, as shown in

$$D_{i,t} = \frac{\hat{Y}_{i,t} - Y_{i,t}}{Y_{i,t}} \times 100 \% \quad (2.4)$$

where  $D_{i,t}$  is the area deviance of land-use type  $i$  at time  $t$ ,  $\hat{Y}_{i,t}$  is the simulated area of land-use type  $i$  at time  $t$ , and  $Y_{i,t}$  is the actual area of land-use type  $i$  at time  $t$ .

The validation results showed that the deviance of forestry and grassland was  $\pm 4$  and  $\pm 3$  %, respectively. While cultivated land and built-up area account for larger shares, the deviance of them is relatively high, but the overall deviance was still controlled within 8 %. Thus, the model can be regarded as robust and can be used to simulate the future land use.

## ***Results***

In this study, we established the county-level net return models of cultivated land, forestry, grassland, and built-up area. And various factors that have effects on the net returns were synthetically incorporated into the basic land-use structure change model. Through the analysis of the historical data, land-use structure change model can quantitatively determine the effect degrees of various factors on the land-use structure changes. Then, as to the simulation of future land-use structure, based on the effect degrees of the factors, such as population, annual per capita income, and price index, the future land-use structure changes can be simulated under different scenarios.

The macroscopic change of the land-use structure during 2010–2050 was simulated under different scenarios, with the water area and unused land integrated into other lands since it is difficult to evaluate them. As to the simulation of land-use scenarios, integrating all the factors that can affect the net returns, according to the assumption of the changes of population and annual per capita income, expected agricultural prices, and grassland production, the future land-use structure changes can be simulated from 2010 to 2050.

Under the BAU scenario (Fig. 2.9), cultivated land and built-up area are still the main land-use types, but cultivated land tends to decrease year by year, and built-up area tends to increase year by year, which is the inevitable requirement of economic development. By 2050, the cultivated land still accounts for the largest proportion. The forestry generally shows a growing trend; the grassland overall shows a trend of decrease; the change of both of land-use types is not obvious; and the amount of forestry and grassland is relatively stable.

Under the REG scenario (Fig. 2.10), during 2010–2050, the area of cultivated land decreases, from 2400 ten thousand hectares to 1500 ten thousand hectares, reducing by 37.5 %. However, there has been a rapid growth in built-up area, the area of which increases from 1250 ten thousand hectares to 2000 ten thousand hectares. The growth rate of built-up area is much higher than that under the BAU scenario (Fig. 2.9) and CES scenario (Fig. 2.11). However, the area of forestry shows a trend of fluctuations with slow increase, and the area of grassland decreases year by year with small amplitude.

Under the CES scenario, we give priority to the protection of development of ecological environmental sustainability. According to the simulation results, the area of cultivated land decreases significantly, while the area of built-up area and woodland area increases year by year, and the area of grassland also shows a trend of decrease, but the trend is not obvious. The decreasing trend of cultivated land

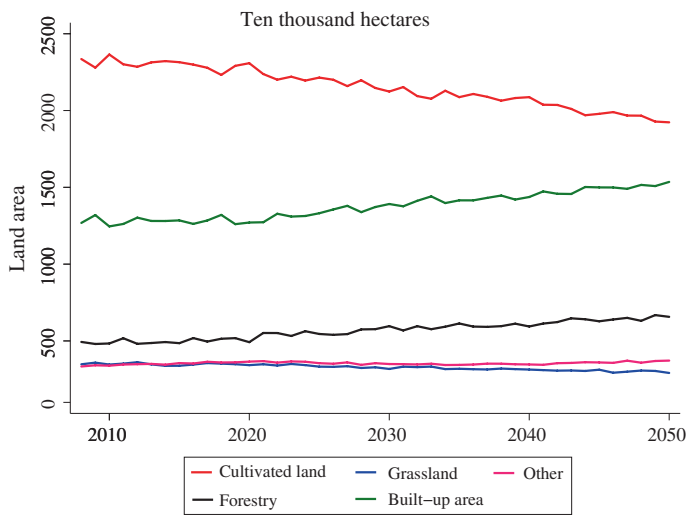


Fig. 2.9 Structure changes of land use under BAU scenario

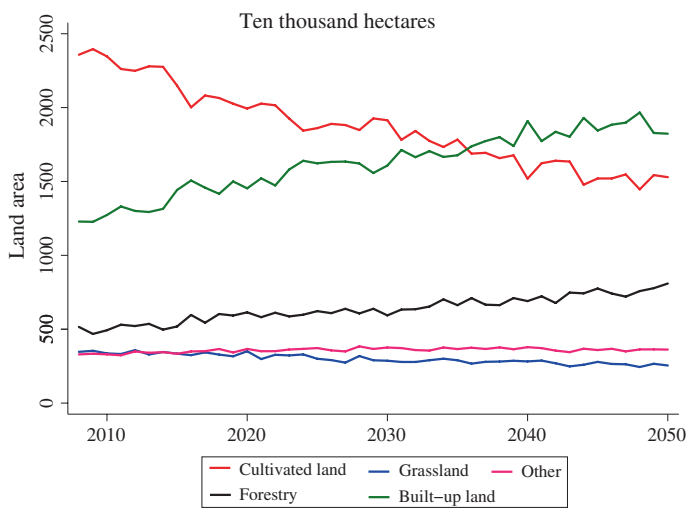


Fig. 2.10 Structure changes of land use under REG scenario

and the expansion trend of built-up area can reach stable balance until 2050, and the area of the forestry continues to increase to maintain the sustainable development of ecological environment.

In general, with the improvement of economic growth rate, the built-up area is increasing year by year, and the decrement rate of cultivated land is also

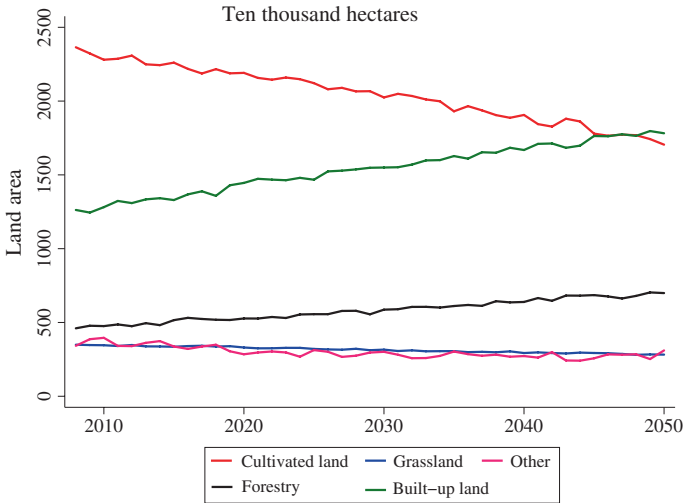


Fig. 2.11 Structure changes of land use under CES scenario

increasing. Under the REG and CES scenarios, the proportion of built-up area in the land system is more than that of the cultivated land by 2050. And under the three different economic growth scenarios, the forestry overall shows a trend of increase, and the growth rate of forestry speeds up as economic growth speeds up. And the grassland overall shows a trend of decrease under the three scenarios.

Summary

The North China Plain is one of the agricultural production bases in China, which is in the important period of increasing population, developing economy, and accelerating urbanization process. In this study, we applied econometric model to analyze the mechanism of county-level land-use structure changes, then simulated the changes of land-use structure from 2010 to 2050 under three scenarios, quantitatively revealed the relationship between the land-use structure changes and the driving factors, and realized the simulation and scenario analysis on structural changes of land use. This relatively sophisticated county-level land-use structure changes simulation method can be applied in other regions, and the conclusions can provide reference for decision making of regional-level land exploitation, planning, and management.

First, comparing the simulation results of future land-use structure changes in the North China Plain of BAU, REG, and CES scenarios, the competition laws among the land-use types under the synthesized effects of various driving factors can be analyzed. Under the BAU scenario, each type of land experience expansion and shrinkage to some extent over time, among which, the cultivated land has an

obvious trend of decrease and the built-up area has an obvious trend of increase. And under the REG and CES scenarios, since the economic growth rates are different, the extents of expansion and shrinkage of different land-use types are also different.

Second, the built-up land overall shows a trend of increase under the three scenarios, with its area increasing from 1260 ten thousand hectares in 2010 to 1500 ten thousand hectares, 1910 ten thousand hectares, and 1820 ten thousand hectares in 2050 under the BAU, REG, and CES scenarios, respectively. Under the REG scenario, the significant increase of the built-up land reflects that the REG can lead to the increase in net return of built-up area and it is important to note that the growth rate of built-up area may be overestimated since the endogenous driving factor urbanization is not taken into consideration. There has been a view that, with the expansion of built-up area, the net return of built-up area will decline, thus, to limit the continual expansion of built-up area. In addition, the increase in the net return of built-up area could lead to the increase of urban housing density and further affect land-use structure, while the housing factor is also not taken into consideration in this model. Thus, the absence of these factors may limit the accuracy of the simulation results of land-use structure in these models.

Third, the structural change trends of land use under the three scenarios are relatively consistent, with cultivated land showing a trend of decrease and built-up area showing a trend of increase. It indicates that urbanization in the North China Plain is one of the main driving factors of land-use structure changes. According to the simulation results, cultivated land, as the main land-use type in the North China Plain, accounting for the largest proportion, decreases with the improvement of economic growth. Under the REG scenario, the area of cultivated land will be less than that of built-up land by 2050.

Finally, the simulation results of land-use structure changes under the three scenarios can provide significant reference for making land-use planning and sustainable development strategy of government. On the whole, the cultivated land will decrease and built-up area will increase with the economic development, which may lead to contradiction between cultivated land, food security, and improvement in our living standard. So, more attentions should be paid to the trade-off between the urban expansion and food security, including the land consolidation and rehabilitation and compensation mechanism for protecting cultivated land.

## **Simulated Shifting Patterns of Agroecological Zones Across China**

### ***Introduction***

The world is facing a crisis in terms of food security (Rosegrant and Cline 2003). The challenge is from not only the growing global population but also the sustainability of nutritious food supply. In order to meet global demands, food production

should increase 60–70 % by 2050 compared with that at the beginning of the twenty-first century (Alexandratos and Bruinsma 2012). Climate change is now widely recognized as one of the most critical influences on sustainability of food supply. It changes the suitability of crop and investment structure in agriculture. Researchers have confirmed that the crop suitability shifts in the context of climate change (Ramirez-Villegas et al. 2013). Lane and Jarvis (2007) predicted the impact of climate change with current and projected future climate data and found that the suitable area of main food crops, including rice, wheat, potato, and some cash crops, such as apple, banana, coffee, and strawberry, would reduce along with climate change. According to the evaluation of Easterling et al. (2007), even in the scenario of Intergovernmental Panel on Climate Change (IPCC) low emissions (B1, with a 2 °C rise in global mean temperatures by 2100), the current farming systems will be destabilized. If the increasing suffering from chronic hunger is frustrating today, the further difficulties, risks, and challenges for achieving food security will make people desperate, especially for those in South Asia and sub-Saharan Africa (Godfray et al. 2010).

China, which experienced rapid growth and increased integration with the global economy in recent years, has significant potential to contribute to global food security not only by alleviating hunger among its own citizens, but also by increasing trade and financial linkages as well as technology and knowledge exchanges with other developing countries (Fan and Brzeska 2010). China has made remarkable progress in reducing poverty, cutting the share of people living on less than \$1.25 a day from 84 % of the population in 1981 to 13 % in 2008 and reducing the number of poor people from 835 million to 174 million (Malik 2013). In recent years, the development of China's agricultural production is very stable which significantly contributes to global security (Huang and Rozelle 2009). But there are still some potential challenges for China's food supply. One of the most probable challenges is climate change. Now and in the future, China's food supply will be a key issue for the world food market.

There are various ways such as the frequency and intensity changes of disasters (including flood, drought, hail, and typhoon) and the changes of precipitation, accumulated temperature, and solar radiation that climate change influencing China's agricultural production. Though most of these influences are occasional and small-scaled, there are still some influences that are persistent and massive (Guo et al. 2014). The variation of AEZs may be one of the most notable responses of climate change that can alter the pattern of crop and agricultural management. The AEZ concept was originally developed by the FAO. It has widespread applications in land-use planning, design of appropriate agricultural adaptations, reducing vulnerability, as well as crop water requirements and long-term frost protection measures determination (Wratt et al. 2006). There are many researches on agro-ecological zoning in China and relevant topics (Deng et al. 2006; Yu et al. 2012). Chen classified China into twelve AEZs based on the mode of agricultural production, the productivity of farmland, heat, water, and landform (Chen 2001). Jin and Zhu divided Northeast China into three AEZs and found that the maize yields are reduced significantly along with climate change (Zhi-Qing and Da-Wei 2008).

Yang et al. applied the method proposed by Chen (2001) to classify Northwest China into thirteen AEZs and analyzed the climate-induced changes in crop water balance in each AEZ (Yang et al. 2008). He et al. divided Chinese wheat-producing area into three major regions and ten AEZs depending on the produced grain traits, ecological factors, soil properties, cropping system, and so on (Zhonghu et al. 2002). On the basis of these ten AEZs, Jia et al. studied the variation of precipitation and found the AEZ-based research help to master the precipitation patterns of different agricultural regions. As a determinant of cropping pattern and agriculture management, the pattern of AEZs may change significantly under the background of global climate change. There is no doubt that an assessment of shifting patterns of AEZs in China is helpful to guide the nation's future agricultural development and guarantee global food security (Jia et al. 2012).

The global agroecological zones (GAEZs) were developed in order to provide a prediction for crop potential productivity in a specific environment under limiting factors including climate and soil. They were used as the main analysis units of agricultural production in Global Trade Analysis Project (GTAP) as well as a lot of other researches. For example, Atehnkeng et al. analyzed the distribution and toxigenicity of *Aspergillus* species isolated from maize kernels from three AEZs in Nigeria (Atehnkeng et al. 2008). Palm et al. analyzed environmental and socioeconomic barriers for plantation activities on local and regional levels and investigated the potential for carbon finance to stimulate the increased rates of forest plantation on wasteland in southern India combined with AEZs (Palm et al. 2011). IIASA and FAO had published the GAEZ version 3.0 aiming to include practical applications such as a significantly updated version, including expanded crop coverage and dryland management techniques. This dataset provides climate change impacts on agroecological suitability and productivity for three time horizons, 2020s, 2050s, and 2080s, for 11 combinations of GCMs and IPCC emission scenarios, which is global significance. But it is a little bit sketchy for guiding national and regional agriculture developments because more detailed and accurate data can always be obtained to support agroecological zoning at such scale. Mugandani et al. reclassified the AEZs of Zimbabwe based on the climatic data from meteorological stations to cover the shortage of GAEZ (Mugandani et al. 2012). Kurukulasuriya and Mendelsohn compared the observed distribution of AEZs from FAO, the calculated distribution of AEZs given climate, and found there were significant local differences (Kurukulasuriya and Mendelsohn 2008). These studies imply that it makes sense to access the impacts of future climate change on shifting patterns of the AEZs by using more detailed and accurate data at regional and national levels.

This study aims to assessing the shifting patterns of AEZs in China driven by future climate change. The major contribution of this study is that it provides future AEZs in China which contains decision-making information for agriculture development in China and global food security. Compared with GAEZ, this study takes full advantage of observed climate data from meteorological stations. And compared with other static assessment results based on historical period data such as Chen (2001), this study provides more predictive information of shifting

patterns of AEZs. In addition, the data processing scheme of integrating observed and predicted data of this study has high reference value for similar studies. AEZs in China of four periods: 2011–2020, 2021–2030, 2031–2040, and 2041–2050 were drawn in this study based on the projected climatic changes. It is found that the future climate change will lead to significant change of AEZs in China, while the overall pattern of AEZs in China is stable. The northward expansion of humid AEZs to subhumid AEZs in south China, eastward expansion of arid AEZs to dry and moist semiarid AEZs in north China, and southward expansion of dry semiarid AEZs to arid AEZs in southwest China are the major characteristics of future AEZs changes in China.

## ***Data and Methodology***

### **Agroecological Zoning Methodology**

The AEZ is a zone characterized by specific length of growing period (LGP) and climatic attributes. Several agroecological zoning methods have been previously used for agricultural purposes (Sys et al. 1991). The Center for Sustainability and the Global Environment (SAGE) at the University of Wisconsin derived six global LGPs by aggregating the IIASA/FAO GAEZ data into six categories of approximately 60 days per LGP: (1) LGP1: 0–59 days, (2) LGP2: 60–119 days, (3) LGP3: 120–179 days, (4) LGP4: 180–239 days, (5) LGP5: 240–299 days, and (6) LGP6: more than 300 days (Ramankutty et al. 2004). These six LGPs roughly divide the world along humidity gradients, in a manner that is generally consistent with previous studies in global agroecological zoning (Alexandratos 1995). They are calculated as the number of days with sufficient temperature and precipitation/soil moisture for growing crops. In other words, LGPs are calculated as the number of days in the year when average daily temperature ( $T_a$ ) and precipitation plus moisture stored in the soil ( $P$ ) are above their thresholds. In GAEZ, three standard temperature thresholds for temperature growing periods are used: (1) periods with  $T_a > 0\text{ }^{\circ}\text{C}$ , (2) periods with  $T_a > 5\text{ }^{\circ}\text{C}$ , which is considered as the period conducive to plant growth and development, and (3) periods with  $T_a > 10\text{ }^{\circ}\text{C}$ , which is used as a proxy for the period of low risks for late and early frost occurrences. In this study, we choose the second standard temperature threshold ( $T_a > 5\text{ }^{\circ}\text{C}$ ) for calculating LGPs in China. We set the threshold of precipitation plus moisture stored in the soil as half the potential evapotranspiration (ET) ( $P > 0.5\text{ ET}$ ) to keep it consistent with FAO (Doorenbos and Kassam 1979). Therefore, LGP used in this study is defined as follows:

$$\text{LGP} = \text{Card}\{ (T_a, P_i) | T_a > 5\text{ }^{\circ}\text{C}, P_i > 0.5\text{ ET}_i \} \quad (2.5)$$

where  $T_a$  ( $^{\circ}\text{C}$ ) is the average daily temperature of the  $i$ th day in the year,  $P_i$  ( $\text{mm day}^{-1}$ ) is the precipitation plus moisture stored in the soil of the  $i$ th day in

the year,  $ET_i$  (mmday<sup>-1</sup>) is ET of the  $i$ th day in the year, and Card is the cardinality function counting the number of elements of a set.

In addition to the LGP breakdown, the world is subdivided into three climatic zones, tropical, temperate, and boreal, using criteria based on absolute minimum temperature and growing degree days (GDD), as described by Ramankutty and Foley (1999). Concretely, the climatic zone rules are as follows:

$$\text{zone} = \begin{cases} \text{tropical,} & \text{if } t_{\min} > 0\text{ }^{\circ}\text{C} \\ \text{temperate,} & \text{else if } t_{\min} > -45\text{ }^{\circ}\text{C and } GDD_5 > 1200 \\ \text{boreal,} & \text{else} \end{cases} \quad (2.6)$$

where  $t_{\min}$  (°C) is the absolute minimum temperature, and  $GDD_5$  is the annual number of accumulated GDD above 5 °C.  $GDD_5$  is calculated by taking the average of the daily maximum and minimum temperatures compared to the base temperature, 5 °C.

$$GDD_5 = \sum_{i=1}^{365} \left( \frac{Td_{i,\min} + Td_{i,\max}}{2} - Td_{\text{base}} \right) \quad (2.7)$$

where  $Td_{i,\min}$  and  $Td_{i,\max}$  are the daily maximum and minimum temperatures, respectively;  $Td_{\text{base}}$  (=5 °C) is the base temperature. We employ the definition of AEZs used in the GTAP land-use database, which divides the world into 18 AEZs (Table 2.6).

Data and Process

Both observed and projected climate data were used in this research to assess the shifting patterns of AEZs in China driven by climatic changes. This dataset includes climatic data, moisture stored in the soil, and ET. Historically observed climate data including average daily temperature, precipitation, absolute minimum

Table 2.6 Definition of agroecological zones used in Global Trade Analysis Project

| AEZs  | LGP     | Climatic zone | AEZs  | LGP     | Climatic zone |
|-------|---------|---------------|-------|---------|---------------|
| AEZ1  | 0–59    | Tropical      | AEZ4  | 180–239 | Tropical      |
| AEZ7  |         | Temperate     | AEZ10 |         | Temperate     |
| AEZ13 |         | Boreal        | AEZ16 |         | Boreal        |
| AEZ2  | 60–119  | Tropical      | AEZ5  | 240–299 | Tropical      |
| AEZ8  |         | Temperate     | AEZ11 |         | Temperate     |
| AEZ14 |         | Boreal        | AEZ17 |         | Boreal        |
| AEZ3  | 120–179 | Tropical      | AEZ6  | ≥300    | Tropical      |
| AEZ9  |         | Temperate     | AEZ12 |         | Temperate     |
| AEZ15 |         | Boreal        | AEZ18 |         | Boreal        |

temperature, and daily maximum and minimum temperatures were collected by the China Meteorological Administration for the year 2006. The spline interpolation method is used to interpolate these data using a 100-m digital elevation model developed by Chinese Academy of Sciences. This interpolative method is selected because it takes into account the climatic dependence on topography by using a trivariate function of latitude, longitude, and elevation (Deng et al. 2008b, 2011) and balances the smoothness of fitted surfaces and the fidelity of the data by minimizing the generalized cross-validation automatically (Tait et al. 2006). Observed data of moisture stored in the soil come from soil categories and soil composite datasets at the scale of 1:1,000,000. This dataset was developed according to the survey results of the second national soil census data, covering 1572 soil profiles in 100-cm-depth layer. The ET data come from the MODIS (Moderate Resolution Imaging Spectroradiometer) Global Evapotranspiration Project (MOD16). This project aims to estimate global terrestrial evapotranspiration by using satellite remote sensing data. The missing values of ET data are complemented using the spline interpolation method.

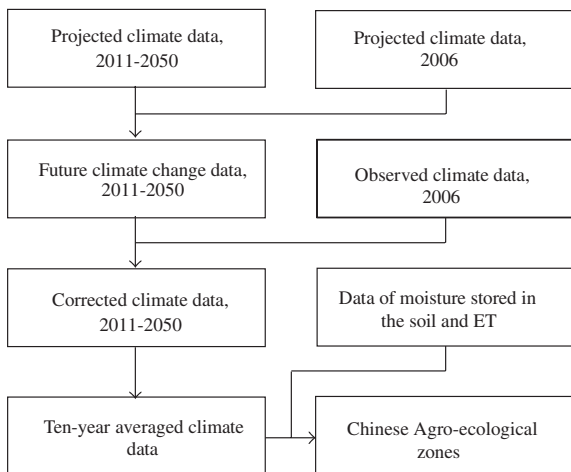
The projected climate data including average daily temperature, daily precipitation, absolute minimum temperature, and daily maximum and minimum temperatures from 2006 to 2050 comes from the datasets produced from Hadley Center coupled model version 3 (HadCM3) GCM (Global Circulation Model) under greenhouse gas emission scenario of B2. The B2 scenario describes a world in which the emphasis is on local solutions to economic, social, and environmental sustainability. While the scenario is also oriented toward environmental protection and social equity, it focuses on local and regional levels. The data are originally obtained with a spatial resolution of  $2.50^\circ \times 3.75$  and downscaled to  $1 \text{ km} \times 1 \text{ km}$  using the spline interpolation method. A data processing scheme is designed to reduce systematic errors generated by HadCM3 and improve the assessment accuracy of the shifting patterns of AEZs in China (Fig. 2.12). First, the changes of average daily temperature, daily precipitation, absolute minimum temperature, and daily maximum and minimum temperatures of each year from 2011 to 2050 compared with those of 2006 are calculated using the projected climate data:

$$\Delta K_{i,y} = K_{i,y} - K_{i,2006} \quad (2.8)$$

where  $K_{i,2006}$  refers to the projected average daily temperature, daily precipitation, daily maximum and minimum temperatures of the  $i$ th day, and absolute minimum temperature, in 2006;  $K_{i,y}$  ( $y = 2011, 2012, \dots, 2050$ ) refers to the projected average daily temperature, daily precipitation, daily maximum and minimum temperatures of the  $i$ th day, and absolute minimum temperature, in the  $y$ th year; and  $\Delta K_{i,y}$  refers to the changes of average daily temperature, daily precipitation, absolute minimum temperature, and daily maximum and minimum temperatures of each year from 2011 to 2050 compared with those of 2006. Second, the corrected climate data can be generated by adding  $\Delta K_{i,y}$  to the observed climate data of 2006.

$$Q_{i,y} = Q_{i,2006} + \Delta K_{i,y} \quad (2.9)$$

**Fig. 2.12** Data processing scheme for assessing the shifting patterns of agroecological zones in China



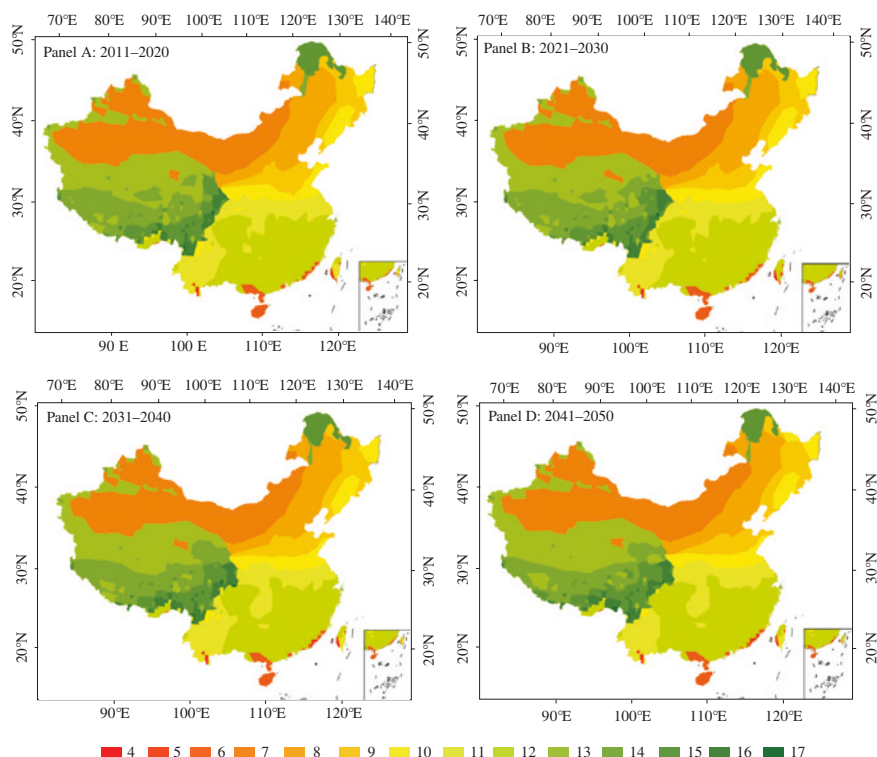
where  $Q_{i,2006}$  refers to the observed average daily temperature, daily precipitation, daily maximum and minimum temperatures of the  $i$ th day, and absolute minimum temperature, in 2006; and  $Q_{i,y}$  refers to the corrected average daily temperature, daily precipitation, daily maximum and minimum temperatures of  $i$ th day, and absolute minimum temperature, in the  $y$ th year. By these two steps, the systematic errors in projected climate data generated by HadCM3 are reduced. Considering climate change is a long-term shift in weather conditions, we then take the average for ten years of the corrected climate data to assess the shifting patterns of AEZs driven by future climate change.

$$Q_{i,p-(p+9)} = \frac{1}{10} \sum_{y=p}^{p+9} Q_{i,y} \quad (2.10)$$

where  $Q_{i,p-(p+9)}$  ( $p = 2011, 2021, 2031, 2041$ ) refers to the ten-year averaged climate data including average daily temperature, daily precipitation, daily maximum and minimum temperatures of the  $i$ th day, and absolute minimum temperature, in the periods of 2011–2020, 2021–2030, 2031–2040, and 2041–2050. Finally, future AEZs in China are obtained with the ten-year averaged climate data and data of moisture stored in the soil and ET.

## Results and Discussion

The assessment results show that there are totally fourteen AEZs in China, most of which will experience pattern shifting from 2011 to 2050 (Fig. 2.13). The AEZ4, AEZ5, and AEZ6 characterized by tropical climate will be mainly found in the extreme south of China (Fig. 2.13). The AEZ4 will be stable in pattern and area



**Fig. 2.13** Future agroecological zones in China, 2011–2050

over time and covers 0.16 million ha, and this translates to no more than 0.02 % of the whole country (Table 2.7). The area of AEZ5 will increase from 1.08 million hectares to 1.76 million ha from 2011 to 2050 with an area expansion of 63.73 %. This area increase will mainly happen in the period of 2021–2040. The new area of AEZ5 will be mainly transferred from AEZ6 (Table 2.8). The AEZ6 will experience an area decreasing from 10.44 to 9.57 million ha during the period from 2011 to 2050 (Table 2.7). Besides the conversion to AEZ5, the area decrease of AEZ6 will be also due to the southward expansion of AEZ11 (Table 2.8; Fig. 2.13).

The AEZ11 and AEZ12 will occupy most area of south China (Fig. 2.13). The AEZ12 will cover about 16 % of the whole of China and expand by 3.88 million ha from 2011 to 2050 (Table 2.7). This expansion will be mainly because of the westward expansion being larger than the southward shrink of AEZ12 (Fig. 2.13). And the newly added area of AEZ11 cannot counterbalance the reduced area from AEZ12 expansion (Table 2.8). Consequently, the area of AEZ11 will reduce from 85.50 million ha in 2011 to 82.48 million ha in 2050 (Table 2.7). Moreover, the northward movement of northern side boundary of AEZ11 implies that there will be LGP reduction that happened in central China. The area of

**Table 2.7** Areas of future agroecological zones in China

| AEZs  | Area ( <i>unit</i> million hectares) |           |           |           |
|-------|--------------------------------------|-----------|-----------|-----------|
|       | 2011–2020                            | 2021–2030 | 2031–2040 | 2041–2050 |
| AEZ4  | 0.16                                 | 0.16      | 0.16      | 0.16      |
| AEZ5  | 1.08                                 | 1.08      | 1.71      | 1.76      |
| AEZ6  | 10.44                                | 11.08     | 9.62      | 9.57      |
| AEZ7  | 200.23                               | 199.37    | 203.73    | 207.76    |
| AEZ8  | 90.05                                | 89.85     | 85.72     | 83.41     |
| AEZ9  | 60.26                                | 58.38     | 60.29     | 60.53     |
| AEZ10 | 53.52                                | 55.80     | 48.39     | 47.34     |
| AEZ11 | 85.50                                | 81.78     | 88.18     | 82.48     |
| AEZ12 | 151.90                               | 155.90    | 149.59    | 155.78    |
| AEZ13 | 141.05                               | 136.86    | 143.84    | 156.05    |
| AEZ14 | 86.57                                | 90.65     | 88.98     | 74.27     |
| AEZ15 | 55.60                                | 53.83     | 51.94     | 52.64     |
| AEZ16 | 15.96                                | 17.58     | 19.71     | 20.10     |
| AEZ17 | 0.49                                 | 0.49      | 0.96      | 0.97      |

AEZ10 will decline from 53.52 to 47.34 million ha from 2011 to 2050 mainly due to the southward expansion of AEZ11 in central China and the expansion of AEZ9 in northwest China (Table 2.8). The center of gravity of AEZ9 will shift to the east due to the overall northward movement of AEZ10, but its area which is about 60.00 million ha will keep stable (Table 2.7).

Most of the area of northern China will belong to AEZ7 and AEZ8 (Fig. 2.13). The AEZ7 will cover 200.23 million ha in the period of 2011–2020 and expand to 207.76 million ha in the period of 2041–2050 (Table 2.7). This area increase is mainly because of the conversion from AEZ8 to AEZ7 (Table 2.8). And there will be significant area reduction of AEZ7 due to the expansion of AEZ13 in northwest China (Table 2.8). The area of AEZ8 will decrease from 90.05 to 83.41 million ha from 2011 to 2050 mainly due to the eastward expansion of AEZ7 (Table 2.7 and Fig. 2.13). The boundary change of AEZ7 and AEZ8 implies that there will be LGP reduction in northern China and temperature decrease in northwest China. Another significant change in northeast China will be the area reduction of AEZ15 (Table 2.7 and Fig. 2.13). About one-fifth of the AEZ15 in northeast China will convert to AEZ8, AEZ9, and AEZ10 due to temperature rise (Table 2.8).

The AEZ13 will cover about 15 % of the whole China and more than a half of southwest China (Table 2.7 and Fig. 2.13). Its area will expand by 15.00 million ha from 2011 to 2050 mainly due to the conversion from AEZ14 (Table 2.8). This indicates that the LGP in southwest China will be generally increased driven by future climate change. And AEZ14 will become more continuous along with climate change (Fig. 2.13). The total area of AEZ15 will be reduced by 2.95 million ha mainly due to its area decrease in northeast China (Table 2.7 and Fig. 2.13). The AEZ16 and AEZ17 will mainly spread over southwest China

**Table 2.8** Transition matrix of agroecological zones in China (*unit* million hectares)

| Transition from |   | Transition to                          |                   |                                        |                                        |                                                             |                                        |                                                             |                                                             |                   |                                                             |                                        |                                        |                   |                                        |
|-----------------|---|----------------------------------------|-------------------|----------------------------------------|----------------------------------------|-------------------------------------------------------------|----------------------------------------|-------------------------------------------------------------|-------------------------------------------------------------|-------------------|-------------------------------------------------------------|----------------------------------------|----------------------------------------|-------------------|----------------------------------------|
|                 |   | AEZ4                                   | AEZ5              | AEZ6                                   | AEZ7                                   | AEZ8                                                        | AEZ9                                   | AEZ10                                                       | AEZ11                                                       | AEZ12             | AEZ13                                                       | AEZ14                                  | AEZ15                                  | AEZ16             | AEZ17                                  |
| AEZ4            | – |                                        |                   |                                        |                                        |                                                             |                                        |                                                             |                                                             |                   |                                                             |                                        |                                        |                   |                                        |
| AEZ5            |   | –                                      | 0.25 <sup>c</sup> |                                        |                                        |                                                             |                                        |                                                             |                                                             |                   |                                                             |                                        |                                        |                   |                                        |
| AEZ6            |   | 0.63 <sup>b</sup><br>0.30 <sup>c</sup> | –                 |                                        |                                        |                                                             |                                        |                                                             | 0.42 <sup>b</sup>                                           | 0.40 <sup>b</sup> |                                                             |                                        |                                        |                   |                                        |
| AEZ7            |   |                                        |                   | –                                      |                                        |                                                             |                                        |                                                             |                                                             |                   | 2.44 <sup>a</sup><br>3.29 <sup>b</sup><br>2.14 <sup>c</sup> |                                        |                                        |                   |                                        |
| AEZ8            |   |                                        |                   | 6.63 <sup>b</sup><br>5.08 <sup>c</sup> | –                                      | 0.72 <sup>b</sup>                                           |                                        |                                                             |                                                             |                   | 0.31 <sup>b</sup>                                           | 0.20 <sup>a</sup><br>0.87 <sup>b</sup> |                                        |                   |                                        |
| AEZ9            |   |                                        |                   |                                        | 3.29 <sup>b</sup><br>2.77 <sup>c</sup> | –                                                           | 3.37 <sup>a</sup><br>1.17 <sup>c</sup> |                                                             |                                                             |                   |                                                             |                                        | 0.21 <sup>b</sup>                      |                   |                                        |
| AEZ10           |   |                                        |                   |                                        |                                        | 1.09 <sup>a</sup><br>4.37 <sup>b</sup><br>2.30 <sup>c</sup> | –                                      | 2.82 <sup>b</sup><br>1.02 <sup>c</sup>                      |                                                             |                   |                                                             |                                        | 0.24 <sup>b</sup>                      |                   |                                        |
| AEZ11           |   |                                        | 0.24 <sup>a</sup> |                                        |                                        |                                                             |                                        | –                                                           | 4.68 <sup>a</sup><br>0.24 <sup>b</sup><br>7.85 <sup>c</sup> |                   |                                                             |                                        | 0.44 <sup>b</sup><br>0.24 <sup>c</sup> | 0.28 <sup>b</sup> | 0.47 <sup>b</sup><br>0.29 <sup>c</sup> |
| AEZ12           |   |                                        | 0.40 <sup>a</sup> |                                        |                                        |                                                             |                                        | 0.57 <sup>a</sup><br>8.81 <sup>b</sup><br>1.66 <sup>c</sup> | –                                                           |                   |                                                             |                                        |                                        | 0.26 <sup>b</sup> |                                        |

(continued)

Table 2.8 (continued)

|       | Transition to |      |      |                                                             |                   |                                                             |                   |                                        |                   |                                                               |                                                             |                                                             |                                                             |                   |  |  |
|-------|---------------|------|------|-------------------------------------------------------------|-------------------|-------------------------------------------------------------|-------------------|----------------------------------------|-------------------|---------------------------------------------------------------|-------------------------------------------------------------|-------------------------------------------------------------|-------------------------------------------------------------|-------------------|--|--|
|       | AEZ4          | AEZ5 | AEZ6 | AEZ7                                                        | AEZ8              | AEZ9                                                        | AEZ10             | AEZ11                                  | AEZ12             | AEZ13                                                         | AEZ14                                                       | AEZ15                                                       | AEZ16                                                       | AEZ17             |  |  |
| AEZ13 |               |      |      | 1.58 <sup>a</sup><br>1.02 <sup>b</sup><br>1.10 <sup>c</sup> |                   |                                                             |                   |                                        |                   | –                                                             | 5.53 <sup>a</sup><br>9.81 <sup>b</sup>                      | 2.61 <sup>a</sup><br>0.25 <sup>b</sup><br>3.12 <sup>c</sup> |                                                             |                   |  |  |
| AEZ14 |               |      |      |                                                             | 0.91 <sup>b</sup> |                                                             |                   |                                        |                   | 3.10 <sup>a</sup><br>14.43 <sup>b</sup><br>13.74 <sup>c</sup> | –                                                           | 1.41 <sup>a</sup><br>2.00 <sup>b</sup><br>0.98 <sup>c</sup> |                                                             |                   |  |  |
| AEZ15 |               |      |      |                                                             | 0.20 <sup>b</sup> | 0.40 <sup>a</sup><br>0.32 <sup>b</sup><br>1.88 <sup>c</sup> | 1.10 <sup>c</sup> | 0.27 <sup>a</sup>                      |                   | 0.02 <sup>b</sup><br>0.55 <sup>c</sup>                        | 2.86 <sup>a</sup><br>3.54 <sup>b</sup><br>0.01 <sup>c</sup> | –                                                           | 2.26 <sup>a</sup><br>3.78 <sup>b</sup><br>0.72 <sup>c</sup> |                   |  |  |
| AEZ16 |               |      |      |                                                             |                   |                                                             |                   | 0.35 <sup>a</sup><br>0.40 <sup>b</sup> | 0.29 <sup>a</sup> |                                                               | 1.45 <sup>b</sup>                                           | 2.83 <sup>b</sup>                                           | –                                                           | 0.33 <sup>c</sup> |  |  |
| AEZ17 |               |      |      |                                                             |                   |                                                             |                   |                                        |                   |                                                               |                                                             | 0.61 <sup>c</sup>                                           |                                                             | –                 |  |  |

Notes <sup>a</sup>From period of 2011–2020 to period of 2021–2030  
<sup>b</sup>From period of 2021–2030 to period of 2031–2040  
<sup>c</sup>From period of 2031–2040 to period of 2041–2050

(Fig. 2.13). The AEZ16 will cover 15.96 million ha in the period of 2011–2020 and expand to 20.10 million ha in the period of 2041–2050 (Table 2.7). These newly expanded areas of AEZ16 will mainly come from AEZ15 (Table 2.8). The area of AEZ17 in China will be almost doubled due to future climate change though it will still cover an area of not more than 1 million ha (Table 2.7).

On the whole, the pattern of AEZs in China will change significantly due to future climate change. The changed area will reach 32.00 million ha accounting for 3.36 % of the country's total area (Table 2.8). Certainly, the changes of AEZs in China are not monotonous. The direction inversion of boundary movement of AEZ12 in southwest China from the period of 2011–2040 to the period 2041–2050 is one of the most prime examples of such changes (Fig. 2.13). But the overall change trend of AEZs in China including northward expansion in south China, eastward expansion in north China, and southward expansion in southwest China is persistent. These results are obtained using datasets produced from HadCM3 under greenhouse gas emission scenario of B2. It is sure that some new results will be found by applying dataset from other models and scenarios. And we will address them in future studies.

## Summary

The shifting patterns of AEZs in China driven by climatic changes were assessed. The projected climate data and historically observed climate data as well as moisture stored in the soil and ET data are used in this study. By using the agroecological zoning methodology proposed by IIASA and FAO, we draw AEZs in China of each of the four periods: 2011–2020, 2021–2030, 2031–2040, and 2041–2050. The main conclusions from this study could be summarized as follows. (i) The overall pattern of AEZs in China will be stable in the future. The AEZ4, AEZ5, and AEZ6 will distribute mainly in the extreme south of China. The AEZ12, AEZ11, AEZ10, AEZ9, AEZ8, and AEZ7 will sequentially spread from north to south. The AEZ13 and AEZ14 will occupy most of the southwest of China. And besides AEZ15 partly distributing in the northeast of China, most of other AEZs (including AEZ15, AEZ16, and AEZ17) will distribute mainly in the southwest of China. (ii) The future climate change will lead to significant local changes of AEZs in China. The changes of AEZs will be not monotonous over time, but the overall change trend of AEZs is persistent. The future change of AEZs in China is characterized by area expansion of AEZ7, AEZ12, AEZ13, and AEZ16 and area reduction of AEZ8, AEZ10, AEZ11, AEZ14, and AEZ15. The shifting patterns of AEZs in China are characterized by northward expansion of humid AEZs to sub-humid AEZs in south China, eastward expansion of arid AEZs to dry and moist semiarid AEZs in north China, and southward expansion of dry semiarid AEZs to arid AEZs in southwest China. (iii) The data processing scheme proposed in this study is helpful in reducing systematic errors in projected climate data which has high reference value for similar studies. Its feasibility has been proved by our

empirical analysis. The application of observed data from meteorological stations will improve the assessment accuracy of impacts of future climate change on shifting patterns of the AEZs in principle.

## References

- Alexandratos N (1995) World agriculture: towards 2010: an FAO study, Food & Agriculture Organization, Rome
- Alexandratos N, Bruinsma J (2012) World agriculture towards 2030/2050: the 2012 revision. ESA Work. Pap 3
- Atehnkeng J, Ojiambo PS, Donner M, Ikotun T, Sikora RA, Cotty PJ, Bandyopadhyay R (2008) Distribution and toxigenicity of *Aspergillus* species isolated from maize kernels from three agro-ecological zones in Nigeria. *Int J Food Microbiol* 122(1):74–84
- Bai Z, Dent D (2009) Recent land degradation and improvement in China. *AMBIO J Hum Environ* 38(3):150–156
- Bajocco S, De Angelis A, Perini L, Ferrara A, Salvati L (2012) The impact of land use/land cover changes on land degradation dynamics: a Mediterranean case study. *Environ Manag* 49(5):980–989
- Capozza DR, Helsley RW (1989) The fundamentals of land prices and urban growth. *J Urban Econ* 26(3):295–306
- Chen B (2001) The integrated agricultural resources production capability and population supporting capacity in China. Meteorological Press, Beijing (in Chinese)
- Chen J, Jönsson P, Tamura M, Gu Z, Matsushita B, Eklundh L (2004) A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky-Golay filter. *Remote Sens Environ* 91(3):332–344
- Deng X, Huang J, Rozelle S, Uchida E (2006) Cultivated land conversion and potential agricultural productivity in China. *Land Use Policy* 23(4):372–384
- Deng X, Huang J, Rozelle S, Uchida E (2008a) Growth, population and industrialization, and urban land expansion of China. *J Urban Econ* 63(1):96–115
- Deng X, Su H, Zhan J (2008b) Integration of multiple data sources to simulate the dynamics of land systems. *Sensors* 8(2):620–634
- Deng X, Huang J, Huang Q, Rozelle S, Gibson J (2011) Do roads lead to grassland degradation or restoration? A case study in Inner Mongolia, China. *Environ Dev Econ* 16(06):751–773
- Deng X, Yin F, Lin Y, Jin Q, Qu R (2012) Equilibrium analyses on structural changes of land uses in Jiangxi Province. *J Food Agric Environ* 10(1):846–852
- Deschenes O, Greenstone M (2007) The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *Am Econ Rev* 354–385
- Doorenbos J, Kassam A (1979) Yield response to water. *Irrig Drainage Pap* 33:257
- Easterling W, Aggarwal P, Batima P, Brander K, Bruinsma J, Erda L, Howden M, Tubiello F, Antle J, Baethgen W (2007) Food, fibre, and forest products 3
- Elhag M, Walker S (2009) Impact of climate variability on vegetative cover in the Butana area of Sudan. *Afr J Ecol* 47(s1):11–16
- Fan S, Brzeska J (2010) The role of emerging countries in global food security. IFPRI Policy Brief 15
- FAO (1996) Agro-ecological zoning guidelines. FAO Soils Bulletin, vol 73. Food and agriculture organization of the United Nations, Rome, Italy
- Foley JA, DeFries R, Asner GP, Barford C, Bonan G, Carpenter SR, Chapin FS, Coe MT, Daily GC, Gibbs HK (2005) Global consequences of land use. *Science* 309(5734):570–574
- Godfray HCJ, Beddington JR, Crute IR, Haddad L, Lawrence D, Muir JF, Pretty J, Robinson S, Thomas SM, Toulmin C (2010) Food security: the challenge of feeding 9 billion people. *Science* 327(5967):812–818

- Guo D, Gao Y, Bethke I, Gong D, Johannessen OM, Wang H (2014) Mechanism on how the spring Arctic sea ice impacts the East Asian summer monsoon. *Theor Appl Climatol* 115(1–2):107–119
- Haim D, Alig RJ, Plantinga AJ, Sohngen B (2011) Climate change and future land use in the United States: an economic approach. *Clim Change Econ* 2(01):27–51
- Herrero M, Thornton PK, Gerber P, Reid RS (2009) Livestock, livelihoods and the environment: understanding the trade-offs. *Curr Opin Environ Sustain* 1(2):111–120
- Huang J, Rozelle S (2009) Agricultural development and nutrition: the policies behind China's success. *World Food Programme*
- Izaauralde RC, Rosenberg NJ, Brown RA, Thomson AM (2003) Integrated assessment of Hadley Center (HadCM2) climate-change impacts on agricultural productivity and irrigation water supply in the conterminous United States: part II. Regional agricultural production in 2030 and 2095. *Agric For Meteorol* 117(1):97–122
- Jia SJ, Han SQ, Wang HJ (2012) The research on the pattern of precipitation in Hebei agricultural regions. *Adv Mater Res* 518:4062–4067
- Jiang QO, Deng X, Zhan J, He S (2011) Estimation of land production and its response to cultivated land conversion in North China Plain. *Chin Geogr Sci* 21(6):685–694
- Jiang L, Deng X, Seto KC (2012a) Multi-level modeling of urban expansion and cultivated land conversion for urban hotspot counties in China. *Landscape Urban Plan* 108(2):131–139
- Jiang QO, Deng X, Yan H, Liu D, Qu R (2012b) Identification of food security in the mountainous guyuan prefecture of China by exploring changes of food production. *J Food Agric Environ* 10(1):210–216
- Kurukulasuriya P, Mendelsohn RO (2008) How will climate change shift agro-ecological zones and impact African agriculture? *World Bank Policy Res Working Pap Ser Vol*
- Lane A, Jarvis A (2007) Changes in climate will modify the geography of crop suitability: agricultural biodiversity can help with adaptation. *SAT ejournal* 4(1):1–12
- Li H, Liu Z, Zheng L, Lei Y (2011) Resilience analysis for agricultural systems of north China plain based on a dynamic system model. *Scientia Agricola* 68(1):8–17
- Liu J, Zhang Z, Xu X, Kuang W, Zhou W, Zhang S, Li R, Yan C, Yu D, Wu S (2010) Spatial patterns and driving forces of land use change in China during the early 21st century. *J Geogr Sci* 20(4):483–494
- Lobell DB, Field CB (2008) Estimation of the carbon dioxide (CO<sub>2</sub>) fertilization effect using growth rate anomalies of CO<sub>2</sub> and crop yields since 1961. *Glob Change Biol* 14(1):39–45
- Malik K (2013) Human development report 2013. The rise of the south: human progress in a diverse world. In: *The rise of the south: human progress in a diverse world* (15 March 2013). UNDP-HDRO human development reports
- MEA (2005) *Ecosystems and human well-being: desertification synthesis*. World Resources Institute
- Mugandani R, Wuta M, Makarau A, Chipindu B (2012) Re-classification of agro-ecological regions of Zimbabwe in conformity with climate variability and change. *Afr Crop Sci J* 20(2):361–369
- Nkonya E, Gerber N, von Braun J, De Pinto A (2011) *Economics of land degradation*. IFPRI Issue Brief 68
- Nobre CA, Sellers PJ, Shukla J (1991) Amazonian deforestation and regional climate change. *J Clim* 4(10):957–988
- Palm M, Ostwald M, Murthy IK, Chaturvedi RK, Ravindranath N (2011) Barriers to plantation activities in different agro-ecological zones of Southern India. *Reg Environ Change* 11(2):423–435
- Perez-Garcia J, Joyce LA, McGuire AD, Xiao X (2002) Impacts of climate change on the global forest sector. *Clim Change* 54(4):439–461
- Qu R, Cui X, Yan H, Ma E, Zhan J (2013) Impacts of land cover change on the near-surface temperature in the North China Plain. *Adv Meteorol* 2013

- Ramankutty N, Foley JA (1999) Estimating historical changes in global land cover: croplands from 1700 to 1992. *Glob Biogeochem Cycles* 13(4):997–1027
- Ramankutty N, Hertel T, Lee HL, Rose S (2004) Global land use and land cover data for integrated assessment modeling. In: Book chapter for the Snowmass conference, Snowmass, CO, July
- Ramirez-Villegas J, Jarvis A, Läderach P (2013) Empirical approaches for assessing impacts of climate change on agriculture: the EcoCrop model and a case study with grain sorghum. *Agric For Meteorol* 170:67–78
- Rosegrant MW, Cline SA (2003) Global food security: challenges and policies. *Science* 302(5652):1917–1919
- Schlenker W, Hanemann WM, Fisher AC (2005) Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. *Am Econ Rev* 395–406
- Schlenker W, Roberts MJ (2009) Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proc Nat Acad Sci* 106(37):15594–15598
- Shi W, Tao F, Liu J (2013) Changes in quantity and quality of cropland and the implications for grain production in the Huang-Huai-Hai Plain of China. *Food Secur* 5(1):69–82
- Sohngen B, Mendelsohn R, Sedjo R (2001) A global model of climate change impacts on timber markets. *J Agric Res Econ* 326–343
- Sys C, Van Ranst E, Debaveye J (1991) Land evaluation. Part. II. Methods in land evaluation. *Agric Publ* 7:247
- Tait A, Henderson R, Turner R, Zheng X (2006) Thin plate smoothing spline interpolation of daily rainfall for New Zealand using a climatological rainfall surface. *Int J Climatol* 26(14):2097–2115
- Tucker CJ (1979) Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sens Environ* 8(2):127–150
- Vlek PG, Rodríguez-Kuhl G, Sommer R (2004) Energy use and CO<sub>2</sub> production in tropical agriculture and means and strategies for reduction or mitigation. *Environ Dev Sustain* 6(1–2):213–233
- Wessels K, Prince S, Frost P, Van Zyl D (2004) Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. *Remote Sens Environ* 91(1):47–67
- WMO (2005) Climate and land degradation. World Meteorological Organization
- Wratt D, Tait A, Griffiths G, Espie P, Jessen M, Keys J, Ladd M, Lew D, Lowther W, Mitchell N (2006) Climate for crops: integrating climate data with information about soils and crop requirements to reduce risks in agricultural decision-making. *Meteorol Appl* 13(04):305–315
- Yang Y, Feng Z, Huang HQ, Lin Y (2008) Climate-induced changes in crop water balance during 1960–2001 in Northwest China. *Agric Ecosyst Environ* 127(1):107–118
- Yin RS, Xiang Q, Xu JT, Deng X (2010) Modeling the driving forces of the land use and land cover changes along the Upper Yangtze River of China. *Environ Manage* 45(3):454–465
- Yin F, Deng X, Jin Q, Yuan Y, Zhao C (2014) The impacts of climate change and human activities on grassland productivity in Qinghai Province, China. *Front Earth Sci* 8(1):93–103
- Yu Y, Huang Y, Zhang W (2012) Changes in rice yields in China since 1980 associated with cultivar improvement, climate and crop management. *Field Crops Res* 136:65–75
- Zhang X, Ge Q, Zheng J (2005) Impacts and lags of global warming on vegetation in Beijing for the last 50 years based on remotely sensed data and phenological information. *Chin J Ecol* 24(2):123–130
- Zhi-Qing J, Da-Wei Z (2008) Impacts of changes in climate and its variability on food production in Northeast China. *Acta Agronomica Sinica* 34(9):1588–1597
- Zhonghu H, Zuoji L, Loongjun W (2002) Classification of Chinese wheat regions based on quality. *Scientia Agricultural Sinica* (China)

Impacts of Land-use Change on Ecosystem Services

Zhan, J. (Ed.)

2015, IX, 260 p. 78 illus., 57 illus. in color., Hardcover

ISBN: 978-3-662-48007-6