Predicting China's Land-use Change and Soil Carbon Sequestration under Alternative Climate Change Scenarios

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This paper examines and predicts the effects of climate change and climate extremes on China's land use conversion and soil carbon sequestration under two alternative climate change scenarios. It intends to investigate the following three questions. 1) How did climate factors affect land-use conversion in China from 1988 to 2000 and what was the relative importance of these factors? 2) How would the predicted future climate change pattern affect land-use choice under alternative climate change scenarios? 3) How would the predicted future climate pattern change the spatial distribution of soil organic carbon in China? The study makes two contributions to the literature. First, it integrates climate change, land use conversion, and soil carbon sequestration into a whole model, which facilitates a comprehensive, systematic analysis. Second, it employs a unique dataset, consisting of high-quality Geographic Information System (GIS) data on climate, land use, and soil properties. To the best of our knowledge, no one has used such detailed Chinese data for economic research.

Key words: Land-use change, soil carbon sequestration, climate change

Climate change has greatly altered traditional meteorological patterns in China. For example, the annual average temperature has risen between 0.5 and 0.8 degrees Celsius in the past century. The warming was especially significant in northern region. It has also intensified the hydrological cycle in China since the 1950s, which boosted frequent floods and droughts. Heavy rains became more intense in the south while rainy seasons in the north shrank shorter in duration. Further, extreme climate and weather records have been broken almost every year in the recent two decades. It is predicted that by 2050, the annual average precipitation will increase by 5 to 7 percent and the annual mean temperature will rise within a range of 2.3 to 3.3 degree Celsius in China (The Ministry of Science and Technology of the People's Republic of China, 2007). The economic cost of the expected climatic change and climate extremes will be huge, considering that one-fifth of the world's population are living in the country that might be at risk from widespread droughts, shrinking lake and tundra, severe desertification, and more frequent and possibly more brutal extreme weather and climate events. While scientists and economists have done much research on the contribution of land use and land cover changes (e.g., deforestation, reforestation, desertification, and urbanization) to climate change, there have been limited studies on the feedback effects.

It is of practical importance to analyze the impacts of climate change and climate extremes on land use conversion. Those impacts are complex. For example, a warming climate may make a cold region more attractive to live in, while an increasing frequency of local extreme weather events may impair a region’s amenity. Consequently, the expected urban land value and urban expansion pattern are changed. Rising temperature can also affect agricultural land use. In a recent study, Schlenker and Roberts (2006) identify a robust nonlinear and asymmetric relationship between temperature and crop yields that is consistent across space, time, and crops, by using a unique 55-year panel dataset of crop yields and a fine-scale daily weather dataset covering the United States. Besides, their study shows that yields of three major crops in the United States are predicted to decrease by 25-44% under the slowest warming scenario and 60-79% under the most rapid warming scenario by the end of the century. In addition to urban built-up area and agricultural land, changes in temperature and precipitation will affect forestland and grassland.

The primary goal of this study is to assess and predict the effects of climate change and climate extremes on land use conversion and soil carbon sequestration. To this point, we develop an econometric land use change model and a statistical SOC density model. The two models explicitly capture spatial autocorrelation and spatial heterogeneity. We combine two models with simulated outputs from two alternative climate change scenarios, i.e., SRES (Special Report for Emissions Scenarios) A2 and B2 scenarios. SRES A2 and B2 scenarios were developed by the Intergovernmental Panel on Climate Change (IPCC) in 2000. We set the year of 2000 as the baseline period and intend to investigate the following three questions. 1) How did climate factors affect land-use conversion in China from 1988 to 2000 and what was the relative importance of these factors? 2) How would the predicted future climate change pattern affect land-use choice under alternative climate change scenarios? 3) How would the predicted future climate pattern change the spatial distribution of soil organic carbon in China?

The study area is Mainland China. We apply detailed GIS dataset in the analysis, which comprises four components: climate data, land-use data, geographic data, and socioeconomic data. Specially, data on SRES A2 and B2 scenarios for the time periods 2001-2100 are provided by the Chinese Academic of Agricultural Sciences (CAAS), which generated the climate change scenarios with a spatial 50*50 km resolution using the PRECIS Model (Providing Regional Climates for Impacts Studies). Land-use data are from a unique land cover and land use database provided by the Chinese Academy of Sciences (CAS), which was developed based on the US Landsat TM/ETM images with a spatial resolution of 30 by 30 meters (Liu et al. 2003, Deng et al. 2008). The study makes two contributions to the literature. First, it integrates climate change, land use conversion, and soil carbon sequestration into a whole model, which facilitates a comprehensive, systematic analysis. Second, it employs a unique dataset, consisting of high-quality Geographic Information System (GIS) data on climate, land use, and soil properties. To the best of our knowledge, no one has used such detailed Chinese data for economic research.

The remainder of this paper is arranged as follows. Section 2 discusses land use change model and SOC density model and. Section 3 describes data. Section 4 reports the estimation and simulation results. The final section will generate a discussion on the current results and future work.

The Model

In this section, we develop an econometric land use change model and a statistical SOC density model. The two models explicitly capture spatial autocorrelation and spatial heterogeneity.

Land Use Change Model

Fully understanding China's landownership is helpful to develop a theoretical model of land-use change in the study. Unlike the United States and many European countries, China has no private land. Land can be owned by the state or by village collective, depending on different land use type. For example, all urban land and most forest, grassland, water area, and unused land belong to the state; and all farmland is collectively owned by villagers. Land use is also heavily regulated by the government. The state retains the right to requisition farmland and other collectively owned land for urban construction, industrial development, and transport infrastructure, by paying subsidy to villagers based on the original use of the land. Land requisition is the single type of land ownership transaction.[1]

In this context, land use decision can be made by two types of agents – government (county-level or above) and village collective. They have different concerns: government officials concern their political and economic achievements to get more promotion opportunities, whereas individual villagers concern the net returns to land. We assume that each type of agent (risk-neutral) makes land use decision to maximize her utility. Based on their concerns, the utility of government includes the level of local GDP and image-building projects; while the utility of villagers comprise household income and employment opportunity. There are six alternative uses for each parcel of land: farmland, grassland, forestland, water area, urban area, and unused land. Let k and s be initial and final land use, respectively. We assume that urban development is irreversible, i.e., urban area will never be converted into nonurban uses. Therefore k can be any of five nonurban uses and s can be any of all six uses.

Let $U_{is|k}$ denote the agent's utility from converting land grid i from use k to use s. $U_{is|k}$ can be decomposed into a deterministic component and an unobserved random component: $U_{is|k} = V_{is|k} + \varepsilon_{is|k}$. We use five pixel-level geophysical and four county-level socioeconomic variables to construct the deterministic component $V_{is|k}$. The geophysical

[1] China's land market is generally referred to as land-use right market, which emerged since the amended *Constitution* legalized land-use right transaction in 1988. It contains conveyance market and transfer market of land-use right, where conveyance market is a primary land market where transactions occur between government and land users and transfer market is a secondary land market where transactions occur between land users.

variables are *land productivity*, *precipitation*, *temperature*, the temporal variations in *precipitation* and *temperature*, respectively. They measure agricultural yield potentials. Three more pixel-level geophysical variables designed to capture spatial effects are discussed below. The socioeconomic variables are county *GDP*, *population*, public *agricultural investment*, and *highway density*. County *GDP* and *population* capture household income, *highway density* measures transport costs for household and for conveying agricultural products, and public *agricultural investment* contributes to improving agricultural productivity in the long run. The more theoretical justification of the specification of $V_{is|k}$ is discussed in Appendix A.

The unobserved random component $\varepsilon_{is|k}$ is assumed to follow the type-I extreme value distribution. Under these assumptions, the probability of converting land grid i from use k to use l is:

(1)
$$\begin{aligned} P_{il|k} &= \Pr\left(U_{il|k} > U_{is|k}, \forall\ l \neq s\right) \\ &= \Pr\left(V_{il|k} + \varepsilon_{il|k} > V_{is|k} + \varepsilon_{is|k}, \forall\ l \neq s\right) \\ &= \Pr\left(\varepsilon_{is|k} - \varepsilon_{il|k} < V_{il|k} - V_{is|k}, \forall\ l \neq s\right) \\ &= \frac{e^{V_{il|k}}}{\sum_s e^{V_{is|k}}} \end{aligned}$$

Equation (1) defines a multinomial logit regression model for each starting use k, with a discrete left-hand-side (LHS) variable that equals one when land grid is changed into use l and equals zero otherwise. To avoid redundant parameters, we set the initial use k as reference such that $V_{ik|k} = 0$ by normalizing the corresponding coefficients to zero's. Hence there are five probability equations in the regression for each starting use k. We use maximum likelihood method to maximize the joint probability of multiple land-use choices based on equation (1).

Spatial autocorrelation. Spatial autocorrelation is an important econometric concern when applying contiguous geographic data for empirical analysis. The cost of not correcting for spatial dependence is inefficient (asymptotically unbiased) estimates if the error structure is correlated over space; or inconsistent or biased estimates if land-use choice is spatially interdependent. But in practice it is technically challenging to distinguish between two types of spatial autocorrelation. In a limited dependent variable model true residuals are unobservable, which further raises the difficulty to test for spatial autocorrelation. Kelejian and Prucha (2001) develop a generalized Moran's *I* statistic (asymptotically equivalent to a Lagrange Multiplier statistic) that can used to examine the existence of spatial error correlation. However, in the literature the econometric theory of testing for spatial interdependency of discrete LHS variable is still in its infancy.[2] The potential for spatial dependence in error term is ignored in this paper because the data sets used in estimation are extremely large (with a range of 1499-19488 observations).

To correct for the potential endogeneity resulted from spatial autocorrelation in the dependent variable, we experiment with a approach by adding three geophysical variables – *terrain slope*, *elevation*, and the *neighborhood index* – as instruments to the right hand side (RHS) of the utility equation. We adopt an unlagged structure of *terrain slope* and *elevation* instruments, which differs from the previous studies which use RHS spatial lags in the spatial analysis (Nelson et al. 2001; Nelson and Hellerstein 1997). *Terrain slope* and *elevation* used in this paper can capture the information from grids adjacent to the original location because they are generated from China's digital elevation model (DEM). DEM has taken spatial effects into account when estimating or retrieving the values of

[2] It is because that the test procedure needs to estimate coefficients and spatial autoregressive parameter simultaneously.

other locations during the interpolation process. The *neighborhood index* is designed as a six-dimensional vector based on neighbors in the original dataset. It measures the average of the percent land use coverage of the eight cells surrounding the original location. It is of theoretical significance to include this instrument in the utility equation. For example, in the classic monocentric city model, the location rent of urban land always goes down with the distance from central business district (CBD), ceteris paribus because the lower rent compensates suburban commuters for their pain and commuting costs. The surrounding urban use coverage is a proxy for the distance from CBD and hence higher coverage tends to reduce commuting costs.

Hence the deterministic component of utility $V_{is|k}$ can be written as

(2) $$V_{il|k} = V\left(x_{il}, \mathbf{y}_i, \mathbf{z}_m\right) = \mu_{l|k} + x_{il}\alpha_{l|k} + \mathbf{y}_i\boldsymbol{\beta}_{l|k} + \mathbf{z}_m{}'\boldsymbol{\gamma}_{l|k} ,$$

where μ_{lk} is transition-specific constant capturing conversion costs.; x_{il} is the *neighborhood index*; $\mathbf{y}_i$ is a vector of variables describing the locational characteristics of grid *i*, such as soil quality, topographic features, and weather conditions; and $\mathbf{z}_m$ is a set of socioeconomic variables indexed by county *m* in respect that county is the most disaggregated unit available for measuring socioeconomic data. The absolute magnitude of coefficient in a multinomial logit model has no economic interpretation. As we discussed in the last paragraph of Section 2.1, we set initial use in *k* as reference and normalize the coefficients so that $\mu_{k|k} = 0$, $\alpha_{k|k} = 0$, $\boldsymbol{\beta}_{k|k} = \mathbf{0}$, and $\boldsymbol{\gamma}_{k|k} = \mathbf{0}$. The normalization avoids an overidentification problem in the regression.

Independence of irrelevant alternatives (IIA). A final econometric consideration pertains to the IIA property of the standard multinomial logit model, i.e., the relative odds of choosing *l* over *k* are independent of the other alternatives. Some studies appeal for more general models (e.g., nested logit model and mixed logit model) to relax IIA assumption (Lubowski et al. 2006; Polyakov and Zhang 2008). But this approach may lead to misspecification or may be infeasible for a large sample. An alternative approach is to employ Hausman specification test to examine IIA property. But even in a well-specified model, Hausman test of IIA often reject the assumption when alternatives seem distinct Cheng and Long (2007). In our study, it is unsatisfactory to apply Hausman test given six land-use alternatives, which requires 15 essential tests for every initial land use ($\frac{6!}{2!\times(6-2)!}=15$). In addition, some applications to land use have demonstrated that IIA assumption is not a serious problem for empirical work (Lewis and Plantinga; Lubowski et al. 2006; Polyakov and Zhang 2008).[3]

SOC Density Model

The dynamics of SOC flow are a complex process, where SOC storage is determined by the balance of carbon inputs from plant production and outputs through a decomposition process (Jobbágy and Jackson 2000; Parton *et al.* 1993; Schlesinger 1977) and soil temperature, moisture, and texture jointly control the decomposition rates of SOC in various carbon pools (Parton *et al.* 1993). The effects of soil temperature and soil moisture on the decomposition rates demonstrate an inverted-U pattern with a heavy left-tail. But the effects of soil texture are much more complicated. For example, sandy soils tend to have higher decomposition rates of active carbon pool and more carbon loss due

[3] Lewis and Plantinga (2007) fail to reject IIA as null hypothesis at the 5% level using Hausman specification test. Lubowski et al. (2006) and Polyakov and Zhang (2008) find that standard models yield qualitatively similar results to general models.

to microbial respiration, whereas an increase in clay content tends to decrease the fraction of carbon flows from slow carbon pool into passive carbon pool and raise the fraction of flows from active carbon pool into passive carbon pool. In addition, studies show that SOC density is negatively correlated with soil bulk density (Wang *et al.* 2004; Wu *et al.* 2003; Yang *et al.* 2007).

While most previous studies typically adopt detailed site-specific biophysical and biochemical models with field-level inputs to estimate soil carbon content, we develop a statistical model to examine the relationship between SOC density and land use through three types of variables – soil property, climate, and land use category. Equation (1) gives a general form of the model.

(3) $$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon},$$

where the bold type denote a vector or a matrix, $\mathbf{y}$ is the dependent variable, the logarithm of SOC density; $\mathbf{X}$ represents independent variables, including land use dummy that is of primary interest, and soil property and climate variables serving as covariates;[4] $\boldsymbol{\beta}$ is coefficient of $\mathbf{X}$; $\boldsymbol{\varepsilon}$ denotes error term. To capture suspect nonlinear effects of soil property and climate variables on the logarithm of SOC density, we adopt a quadratic polynomial functional form of these covariates in the analysis.

There are six land use groups: farmland, forestland, grassland, water area, urban area, and unused land. Soil property variable includes soil PH, soil loam, soil sand and clay contents, and soil bulk density. Climate variables include mean annual precipitation and mean annual temperature. Yang *et al.* (2007) find that such variables can explain 84%

[4] A covariate is a secondary variable that can affect the relationship between the dependent variable and other independent variables of primary interest.

of the variations in SOC storage in China. A nice feature of statistical model is that it has relatively flexible data requirement and can be tailored for specific use. This approach can easily be applied to a large region and hence overcomes the limitation of a detailed site-specific process model.

When applying contiguous geographic data in the empirical study, ordinary least squares (OLS) framework is inappropriate because of suspect spatial variation in parameters and spatially correlated disturbance terms resulted from unobserved “common shocks”. We extend OSL regression of equation (3) to a spatial autoregressive (SAR) model which relaxes independent and identical distribution (IID) assumption and allows for modeling spatial error autocorrelation, and we adopt geographically weighted regress (GWR) technique to capture spatial heterogeneity in coefficients (Fotheringham *et al.* 1998). The model is rewritten as

$$\begin{aligned} \mathbf{y} &= \mathbf{X}\boldsymbol{\beta}(u_i, v_i) + \boldsymbol{\varepsilon}, \\ \boldsymbol{\varepsilon} &= \lambda \mathbf{W}\boldsymbol{\varepsilon} + \boldsymbol{\mu}, \end{aligned} \tag{4}$$

where (u_i, v_i) denotes the coordinates of the i^{th} point in space, $\boldsymbol{\beta}(u_i, v_i)$ is a realization of the continuous function $\boldsymbol{\beta}(u, v)$ at point i, λ is the autoregressive coefficient, $\mathbf{W}$ is a row-standardized $n \times n$ matrix such that $w_{ii} = 0$ and $\sum_{j=1}^{n} w_{ij} = 1$ for each i, $\boldsymbol{\mu}$ is heteroscedastic noise so that $E(\boldsymbol{\mu}\boldsymbol{\mu}') = \sigma^2 \mathbf{M}(u_i, v_i)^{-1}$, and $\mathbf{M}(u_i, v_i)$ is an $n \times n$ diagonal matrix. Hence the error variance-covariance matrix follows as

$$E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}') = \sigma^2 (\mathbf{I} - \lambda \mathbf{W})^{-1} \mathbf{M}(u_i, v_i)^{-1} (\mathbf{I} - \lambda \mathbf{W}')^{-1}. \tag{5}$$

In the spatial model there are two weight matrices, $\mathbf{W}$ and $\mathbf{M}(u_i, v_i)$, respectively used for SAR and GWR approaches. We assume a substantially identical weighting scheme in both matrices, where each non-zero entry is specified as a Gaussian function of geographical distance from point j to point i, as in

(6) $$w_{ij} = \exp\left(-d_{ij}^2 / h^2\right) \Big/ \sum_{j=1}^{n} \exp\left(-d_{ij}^2 / h^2\right), \quad \forall\ i, j = 1, \ldots, n, \text{ and } i \neq j$$

and

(7) $$m_{jj}\left(u_i, v_i\right) = \exp\left(-d_{ij}^2 / h^2\right), \quad \forall\ i, j = 1, \ldots, n.$$

In equations (6) and (7), d_{ij} measures the Euclidean distance between point i and point j and h is referred to as the bandwidth. Another difficulty with the spatial regression is that the estimated parameters are, in part, functions of the weighting function. As the bandwidth h tends to infinity, the weighting function $\left[\exp\left(-d_{ij}^2 / h^2\right)\right]$ tend to one for all pairs of points so that $w_{ij} = (n-1)^{-1}\ \forall j \neq i$ and $m_{jj}\left(u_i, v_i\right) = 0\ \forall\ i, j$. Equivalently, the weights w_{ij} and $m_{jj}\left(u_i, v_i\right)$ becomes uniform for every point j no matter how far it is from location i, and GWR becomes equivalent to SAR. Conversely, as h becomes smaller, the parameter will increasingly depend on observations in close proximity to i. Specially, the weighting function $\left[\exp\left(-d_{ij}^2 / h^2\right)\right]$ tends to zero when the distance d_{ij} is approximately 2.15 times larger than the bandwidth h. The problem is therefore how to select an appropriate bandwidth or decay function in regression. In this study we choose h on a criterion of minimum Predicted Residual Error Sum of Squares (PRESS), where the fitted value with the point i omitted from the calibration process.

The essential idea of GWR is that for each point i there is a bump of influence around i corresponding to the weighting function so that sampled observations near to i have more influence in the estimation of the parameters of i than do sampled observations farther away. We perform weighted least squares regression for each point i in a SAR setting and hence local rather than global parameters can be estimated under the assumption of spatial error autocorrelation. The theoretical coefficient estimates are given by

$$\hat{\boldsymbol{\beta}}(u_i,v_i)=\left[\mathbf{X}'(\mathbf{I}-\lambda\mathbf{W}')\mathbf{M}(u_i,v_i)(\mathbf{I}-\lambda\mathbf{W})\mathbf{X}\right]^{-1}\mathbf{X}'(\mathbf{I}-\lambda\mathbf{W}')\mathbf{M}(u_i,v_i)(\mathbf{I}-\lambda\mathbf{W})\mathbf{y}\ . \tag{8}$$

Data

Our study covers Mainland China. Data used in this paper were provided by the Chinese Academy of Sciences (CAS) and Chinese Academic of Agricultural Sciences (CAAS) including climate, land-use type, terrain, and socioeconomic data. They are measured at a scale of 10 by 10 kilometers, except for socioeconomic data, which are measured at county level. Appendix C provides a detailed summary of the data.

Climate panel data including mean annual *precipitation* and mean annual *temperature* are collected from two sources, where historical observations from 1991 to 2000 are generated from a geographical information system (GIS) database housed in CAS and the simulated climate data for the time periods 2001-2100 are provided by Climate Change Lab, Institute of Environment and Sustainable Development in Agriculture, CAAS. We calculate the standard deviations of mean annual *precipitation* and mean annual *temperature* along time as a measurement of temporal variations in climate. Historical data were initially collected from over 400 weather stations and organized by the Meteorological Observation Bureau of China. CAS interpolated the point climate data into surface data with the method of thin plate smoothing spline Hartkamp et al. (1999) to get more disaggregated information for each pixel. Future climate data were simulated with a spatial 50 by 50 kilometers resolution under two scenarios – SRES (Special Report for Emissions Scenarios) A2 and B2 scenarios, which were developed by the Intergovernmental Panel on Climate Change (IPCC) in 2000. CAAS used Providing Regional Climates for Impacts Studies (PRECIS) Model to generate them. PRECIS is a portable regional climate model HadAM3P developed at the UK Met Office, Hadley Center, and was nested in HadCM3 (abbreviation for *Hadley Center Climate Coupled Model*, *version 3*) general circulation model.

Land-use data are generated from a unique land cover and land use database, which was developed based on the US Landsat TM/ETM images with a spatial resolution of 30 by 30 meters (Deng et al. 2008a; Liu et al. 2003). The data are available for three years – the late 1980s, the mid-1990s, and the late 1990s, denoted as 1988, 1995, and 2000, respectively. CAS made visual interpretation and digitization of TM images to generate thematic maps of land cover, and sorted the data with a hierarchical classification system of 25 land cover classes. Further, CAS grouped 25 classes of land cover into 6 aggregated classes of land use, i.e., farmland, forestland, grassland, water area, urban area[5], and unused land. Deng et al. (2006) provides a detailed explanation of the six land-use types. Table 1a and 1b show land transition matrices of six land-use classes for the time intervals of 1988-1995 and 1995-2000. Land-use exchanges mainly occur between farmland, forestland, and grassland, as well as between grassland and unused land. Urban area expansion is not as significant as anticipated if viewed from a national perspective.

[Table 1a and 1b are about here]

[5] Urban area consists of urban core and other built-up area such as roads, mines, and development zones that are not contiguous with the urban core.

Data on geophysical variables are generated from a geographical information system (GIS) database, including cross-sectional data of *land productivity*, *terrain slope*, and *elevation*. Land productivity is a pixel-specific (5-kilometer-grid) variable, originally estimated by a research team from Institute of Geographical Sciences and Natural Resources Research, CAS by using standalone software of Estimation System for the Agricultural Productivity Deng et al. (2006). Terrain slope and elevation are generated from China's digital elevation model as part of the basic CAS database.

Socioeconomic variables, such as *county GDP* and *population* are gathered from several versions of statistical yearbooks and population yearbooks for China's counties and cities for three years (1989, 1996, and 2000). Data on public *agricultural investment* are collected from province and county level statistical yearbooks for four years (1994, 1995, 1999, and 2000). The investment sources from fiscal budget of the state and local government and is mainly used for developing agriculture infrastructure like seeds, fertilizers, and irrigation. Data on *highway density* are available for one year. Based on a digital map of transportation networks in the mid-1990s, *highway density* are calculated as the total length of all highways in a county divided by land area of that county. Data in value terms are measured at the 2000 real yuan. All of these variables are county-level data.

Results of Estimation and Simulation

Land Use Change Model

We estimate the multinomial logit models with a dataset composed of observations at a 10-*km*-land-grid scale. There are two transition periods of 1988-1995 and 1995-2000 for the analysis. During each period there are five initial land uses (farmland, forestland, grassland, water area, and unused land) and six final uses (farmland, forestland, grassland, water area, urban area, and unused land). So we estimate ten separate models in total. These models perform well, where pseudo R^2 values (McFadden's likelihood ratio index) range between 0.546 and 0.825. We will generate a discussion on the coefficient estimates of climate variables in the models of land-use change on farmland, forestland, and grassland for two transition periods, leaving the remaining estimation results in the Appendix.

Table 2a and 2b report estimation results for the model of land conversion on farmland from 1988 to 1995 and from 1995 to 2000, respectively. Estimates and standard errors of parameters in equation (2) are presented in columns by land-use choice. Specially, positive estimate of a parameter implies that the factor contributes to converting farmland to the corresponding alternative use and vice versa. As is shown the odds of farmland conversion can be affected by climate. For example, a patch of high-rainfall farmland is more likely to be afforested; conversely, a patch of low-rainfall and low-temperature farmland is less likely to be abandoned, i.e., converted to unused land. In contrast to the mean values of rainfall and temperature, the standard deviations of mean annual precipitation and mean annual temperature along time are unstable during two periods. Table 3a and 3b report estimation results for the model of land conversion on forestland from 1988 to 1995 and from 1995 to 2000, respectively. In general, the sign, magnitude, and statistical significance of estimates are consistent in two transition periods. Specifically, low rainfall and high temperature tend to increase the probability of deforestation. As for the temporal variation of precipitation and temperature, we find that large variation in rainfall lowers the odds of converting forestland to farm use; we also find that large variation in temperature tends to increase the propensity of deforestation in the transition period of 1995-2000. The estimation results also provide evidence for the effects of climate variables on land-use change on grassland, as is presented in Table 4a and 4b. For example, a patch of high-rainfall grassland is less likely to be changed to the unused.

[Table 2a and 2b are about here]

[Table 3a and 3b are about here]

[Table 4a and 4b are about here]

Although the results in Table 2a-4b demonstrate the significance of explanatory variables in land-use change decisions, these results say little about the relative importance of these influences. Due to the nonlinear, multinomial form of the model, the importance of the various factors can be discerned only through a series of simulations. Hence we use the empirical multinomial logit models to investigate the effect of climate change on land use conversion. To be specific, we estimate changes in national land hectares for each major use between 1988 and 2000 under five alternative scenarios, including one factual and four counterfactuals described in Table 5a. By using the actual historical values of all variables, the factual simulation provides a benchmark to measure land use changes under alternative counterfactual scenarios. Every counterfactual simulation holds a particular variable at a hypothetical level and keeps the remaining variables at their historically observed values. Simulations are run at a grid level of 10 *km* by 10 *km* (equivalent to 10,000 hectares).

[Table 5a is about here]

Change in the total area for each use between 1988 and 2000 is estimated in the following five steps: 1) using the coefficient estimates of five standard econometric models for 1988-1995 to predict the probabilities of land-use choice of every individual gird in 1995, given the historical use in 1988;[6] 2) using the estimates from five standard models of transition period 1995-2000 to estimate probabilities of land-use choice of each grid cell in 2000, respectively conditional on each of six uses in 1995; 3) multiplying the probabilities predicted in the first step by the conditional probabilities predicted in the second step, and hence obtaining the joint probabilities of land-use choice in 2000 for every individual land cell; 4) summing the land-use choice probabilities by land-use type across individuals and multiplying the summations by 10,000 hectares; 5) calculating the difference between aggregate hectare of each use estimated in the fourth step and the historical land-use hectare in 1988. The procedure is applied to each of five alternative scenarios.

The simulation model performs moderately well in regenerating the direction and relative magnitudes of land-use changes from 1988 to 2000. The factually-simulated land area in 2000 are within a range of 0.03-5.72% of actual totals for each use, exclusive of the situations of unaltered use, in which the factual estimates tend to underestimate the land-use area of the actual value. Table 5b reports the simulation results, where change in hectare is the total land area change for each use between 1988 and 2000, and percent change is the net hectare change under each counterfactual scenario relative to the hectare change under factual scenario. In addition, positive (negative) values indicate that the factor contributes to increasing (decreasing) the land hectare for that use.

[6] For any land grid starting in urban uses, the probabilities of converting to other uses equal zero provided the assumption of irreversible urbanization.

[Table 5b is about here]

Simulation results show that climate factors have a large impact on the land-use change on farmland, forestland, grassland, and unused land during 1988-2000. To be specific, changes in mean annual precipitation and temporal variations around the mean annual precipitation respectively decreased the area of farmland by 32.4% and 233.4%, and increased forestland acreage by 70.5% and 737.9%. Conversely, changes in mean annual temperature and temporal variations around the mean annual temperature increased farmland area by 20.4% and 62.1%, and decreased forestland area by 62.4% and 1861%, respectively. Based on this result two points deserve attention. First, changes in precipitation and temperature play opposite roles in driving conversion of farmland and forestland. Second, farmland and forestland conversions are more sensitive to changes in precipitation so that the role of rainfall change outperforms the role of temperature change. In contrast, climate factors affect conversion of grassland and unused land via a different pattern. Specially, changes in mean annual precipitation and temperature decreased grassland acreage by 32.4% and 233.4%, and increased the area of unused land by 28% and 131.8%, respectively; whereas temporal variations around the mean annual precipitation and mean annual temperature respectively increased grassland area by 39.4% and 476.3%, and decreased unused land area by 389% and 344.1%. Additionally, Table 5b provides strong evidence that the impacts of climate variation around the mean value are much greater than the impacts of climate change in the mean value on land-use change.

SOC Density Model

We calibrate the bandwidth h at 75 *km* using the minimum PRESS criterion. The essential idea is that for each point i there is a "bump of influence" around i with a radius of 161.25 *km* ($161.25km = 75km \times 2.15$); whereas the influence of points beyond the circle on i is negligible. To avoid collinearity caused by land-use dummy, we remove the intercept in the regression, i.e., we set the expected mean value of the pooled sample as a reference. Therefore, the absolute magnitude of coefficient of land-use dummy variable has no economic interpretation. It measures the difference in the expected mean of SOC density for each separate land-use category relative to the reference.

[Figure 1 is about here]

Like the land-use change model, the SOC density model also performs well. Figure 1 demonstrates the histogram of the pooled R^2 with a mean value of 0.633 and a standard deviation of 0.164. The results provide credible evidence for the existence of spatial autocorrelation. We conduct a likelihood ratio test for each model (i.e., each observation). The P-value's are reported to greatly less than 0.001 and the spatial autoregressive parameter, lambda, are uniformly estimated to be 0.999 for all observations.

[Figure 2 is about here]

There is convincing evidence that the SOC density is statistically significantly associated with land-use dummy variable. As is presented in Figure 2, the pooled P-value of this variable is generally within a range of 0-0.1. In particular, it has a mean of 0.032, which is definitely within a 95% confidence interval. It is also instructive to look at the distribution of coefficient estimates of land-use dummy variable, which is plotted in Figure 3 and 4. The estimates greatly vary around the means though the means are close to zero. By summarizing the statistics of these estimates, we find that forestland parameter has the highest mean estimates of 0.0068. It is followed by grassland with the mean value equal to 0.0030. In contrast, the mean estimates of the remaining four types of land uses are reported to be negative and the lowest value is -0.0092 as the mean estimates of unused land.

[Figure 3 is about here]

[Figure 4 is about here]

Discussions

To investigate the effect of future climate change on land conversion and SOC carbon content, we first design a baseline scenario of 2001-2050 based on data in 2000. Under the baseline, we allow GDP growing at a declining rate of less 0.5% for each five-year interval. Data on population growth rate are from U.S. Bureau of the Census, International Data Base. Specially, under the baseline scenario population in China will begin to decrease since 2027. We also assume public agricultural investment growing at an annually constant rate of 3.65%, which is the average growth rate of the investment from 1994 to 2000. Figure 5 gives a description of annual growth rate of GDP and population in the baseline scenario.

[Figure 5 is about here]

Under the baseline, we predict the land area for each use at a national scale, which is reported in Figure 6. It shows that farmland, forestland, and grassland will decrease, while unused land, water, and urban area will increase. By combining the land-use change model with SOC density model, we also estimate future SOC content the baseline scenario as is presented in Figure 7. It is obvious that SOC content will decline because the area of forestland and grassland are predicted to be reduced.

[Figure 6 is about here]

[Figure 7 is about here]

The following work is to generate simulations of land-use change and SOC content under future climate scenarios. We are working on it at present and will finish it by the end of May.

Acknowledgments

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Appendix will be available upon request.

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Table 1a. Land-use Transitions from 1988 to 1995

Initial land-use		Final land-use						
		Farm	Forest	Grass	Water	Urban	Unused	Total
Farm	Freq	11131	2952	1947	386	178	212	16806
	Prob	0.662	0.176	0.116	0.023	0.011	0.013	1
Forest	Freq	2787	15976	2997	161	36	272	22229
	Prob	0.125	0.719	0.135	0.007	0.002	0.012	1
Grass	Freq	1931	2974	21333	336	16	3518	30108
	Prob	0.064	0.099	0.709	0.011	0.001	0.117	1
Water	Freq	415	179	400	1353	28	298	2673
	Prob	0.155	0.067	0.150	0.506	0.010	0.111	1
Urban	Freq	106	29	16	10	160	9	330
	Prob	0.321	0.088	0.048	0.030	0.485	0.027	1
Unused	Freq	246	312	3142	329	11	16026	20066
	Prob	0.012	0.016	0.157	0.016	0.001	0.799	1
Total		16616	22422	29835	2575	429	20335	92212

Table 1b. Land-use Transitions from 1995 to 2000

Initial land-use		Final land-use						
		Farm	Forest	Grass	Water	Urban	Unused	Total
Farm	Freq	12531	2122	1478	253	100	152	16636
	Prob	0.753	0.128	0.089	0.015	0.006	0.009	1
Forest	Freq	2344	17422	2281	145	24	253	22469
	Prob	0.104	0.775	0.102	0.006	0.001	0.011	1
Grass	Freq	1720	2261	22937	302	11	2630	29861
	Prob	0.058	0.076	0.768	0.010	0.000	0.088	1
Water	Freq	235	97	248	1736	12	268	2596
	Prob	0.091	0.037	0.096	0.669	0.005	0.103	1
Urban	Freq	85	15	9	20	305	4	438
	Prob	0.194	0.034	0.021	0.046	0.696	0.009	1
Unused	Freq	188	204	3025	270	7	16665	20359
	Prob	0.009	0.010	0.149	0.013	0.000	0.819	1
Total		17103	22121	29978	2726	459	19972	92359

Table 2a. Coefficient Estimates for the Standard Multinomial Logit Model of Land-use Change on Farmland, 1988-1995

Indep. Variable	Forestland		Grassland		Water area		Urban area		Unused land	
	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Intercept	-2.4944***	(0.2027)	-2.4109***	(0.2505)	-4.0919***	(0.4224)	-6.1098***	(0.7112)	-0.9629	(0.7185)
Land productivity	-0.0570***	(0.0122)	-0.0959***	(0.0144)	-0.0577***	(0.0207)	-0.0457*	(0.0270)	-0.1269***	(0.0320)
County GDP	0.0479***	(0.0167)	0.0623***	(0.0202)	0.0706**	(0.0293)	0.0944***	(0.0332)	-0.0004	(0.0905)
Population	-0.3910***	(0.1031)	-0.6637***	(0.1354)	-0.2232*	(0.1271)	-0.1864	(0.1854)	-0.2542	(0.2555)
Agricultural investment	-0.1021	(0.1508)	-0.0822	(0.1196)	-0.5175	(0.4002)	-0.7971**	(0.3207)	-1.0209	(1.2504)
Highway density	-0.1156***	(0.0296)	-0.1249***	(0.0464)	0.0040	(0.1078)	0.0429	(0.0534)	0.0370	(0.1292)
Terrain slope	0.0541***	(0.0104)	0.0799***	(0.0108)	0.0169	(0.0338)	-0.1900	(0.1186)	-0.0129	(0.0818)
Elevation	0.0950*	(0.0576)	0.1758***	(0.0574)	-0.2773	(0.1733)	0.3259	(0.2554)	-0.7721***	(0.2108)
Precipitation	0.9175***	(0.1924)	-0.0651	(0.2312)	-0.7200*	(0.4004)	0.4239	(0.5523)	-3.0655***	(0.8473)
Temperature	-0.0065	(0.0099)	0.0142	(0.0105)	0.0889***	(0.0244)	0.1137**	(0.0452)	-0.0753***	(0.0223)
Std Err of precipitation	-2.4573***	(0.6117)	-0.6045	(0.9496)	0.0051	(1.1433)	-0.2298	(1.7038)	-0.3552	(4.8060)
Std Err of temperature	-0.9903***	(0.3680)	-0.2820	(0.4576)	-0.5643	(0.8490)	-2.6193**	(1.1561)	-0.7981	(1.3608)
Neighborhood index	0.0511***	(0.0012)	0.0519***	(0.0015)	0.0869***	(0.0032)	0.1032***	(0.0048)	0.0530***	(0.0032)
Number of observations					15012					
McFadden's LRI					0.6436					

Note: *, **, and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 2b. Coefficient Estimates for the Standard Multinomial Logit Model of Land-use Change on Farmland, 1995-2000

Indep. Variable	Forestland		Grassland		Water area		Urban area		Unused land	
	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Intercept	-3.8590***	(0.2606)	-3.2968***	(0.2424)	-4.9410***	(0.6075)	-7.2280***	(0.9423)	-0.4472	(0.8303)
Land productivity	-0.1027***	(0.0136)	-0.1318***	(0.0157)	-0.0510**	(0.0233)	-0.0463	(0.0368)	-0.1482***	(0.0411)
County GDP	0.0026	(0.0081)	-0.0045	(0.0146)	0.0315*	(0.0166)	0.0114	(0.0226)	0.0429**	(0.0208)
Population	0.0379	(0.0947)	-0.3445***	(0.1274)	-0.2059	(0.2344)	0.0661	(0.2134)	-0.7696	(0.5879)
Agricultural investment	-0.1981*	(0.1019)	-0.0524	(0.1141)	-0.2718	(0.2381)	-0.1176	(0.2517)	0.1167	(0.3628)
Highway density	-0.1610***	(0.0504)	-0.1808***	(0.0635)	-0.1645	(0.1513)	-0.0802	(0.1757)	-0.1332	(0.1735)
Terrain slope	0.0726***	(0.0091)	0.0498***	(0.0110)	-0.2091***	(0.0585)	-0.0871	(0.1163)	-0.2446*	(0.1289)
Elevation	0.0780	(0.0591)	0.4166***	(0.0643)	-0.0817	(0.1958)	0.4502*	(0.2462)	-0.3200	(0.2467)
Precipitation	0.6961***	(0.1513)	-0.3161*	(0.1863)	0.8743**	(0.3844)	0.5525	(0.5124)	-4.3673***	(1.0255)
Temperature	-0.0020	(0.0101)	0.0221*	(0.0116)	0.0040	(0.0290)	0.0392	(0.0422)	-0.1388***	(0.0324)
Std Err of precipitation	0.3500	(0.5999)	0.3058	(0.9794)	-0.6821	(1.7468)	-1.5711	(2.9525)	1.3712	(3.3825)
Std Err of temperature	1.0990***	(0.3650)	1.0649***	(0.2832)	1.2361	(0.8399)	1.1539	(1.1732)	-0.6066	(1.1337)
Neighborhood index	0.0419***	(0.0013)	0.0383***	(0.0015)	0.0567***	(0.0037)	0.0980***	(0.0064)	0.0438***	(0.0040)
Number of observations					14794					
McFadden's LRI					0.6662					

Note: *, **, and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 3a. Coefficient Estimates for the Standard Multinomial Logit Model of Land-use Change on Forestland, 1988-1995

Indep. Variable	Farmland		Grassland		Water area		Urban area		Unused land	
	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Intercept	-2.7835***	(0.1834)	-3.0779***	(0.1945)	-4.6856***	(0.7387)	-4.4508***	(1.6021)	-3.8801***	(0.8209)
Land productivity	-0.0065	(0.0130)	0.0566***	(0.0170)	0.0691	(0.0430)	-0.1788	(0.1189)	0.0345	(0.0934)
County GDP	0.0027	(0.0147)	0.0182	(0.0225)	-0.1406	(0.0966)	0.0157	(0.0574)	0.0414	(0.0781)
Population	-0.0550	(0.0930)	-0.0021	(0.1321)	0.8228**	(0.4039)	0.2045	(0.4704)	0.2703	(0.6201)
Agricultural investment	0.0491	(0.0886)	-0.1197	(0.1150)	0.2975	(0.6051)	1.1349*	(0.6332)	0.3852	(0.4356)
Highway density	0.1676***	(0.0498)	0.1716***	(0.0567)	0.1136	(0.2419)	-0.3792	(0.8857)	0.3911**	(0.1587)
Terrain slope	-0.0243***	(0.0072)	-0.0095	(0.0062)	-0.2402***	(0.0435)	-0.2248*	(0.1173)	-0.0552*	(0.0322)
Elevation	-0.1688***	(0.0500)	0.1285***	(0.0322)	-0.5179***	(0.1666)	-2.8689***	(0.6227)	0.1158	(0.1030)
Precipitation	-0.4353***	(0.1574)	-1.0997***	(0.1715)	-0.7107	(0.6314)	-1.0955	(1.3883)	-2.3025***	(0.8236)
Temperature	0.0507***	(0.0084)	0.0301***	(0.0068)	0.0771**	(0.0323)	0.0790	(0.0784)	-0.1096***	(0.0279)
Std Err of precipitation	-1.6625***	(0.4919)	1.3443**	(0.6553)	-0.6897	(1.9371)	-1.0067	(4.6230)	-0.4653	(4.4423)
Std Err of temperature	-0.1248	(0.3061)	0.5206	(0.3607)	-0.3588	(1.3495)	-0.4862	(3.2093)	0.3350	(1.5463)
Neighborhood index	0.0576***	(0.0013)	0.0583***	(0.0012)	0.1132***	(0.0056)	0.1507***	(0.0138)	0.0793***	(0.0040)
Number of observations					19345					
McFadden's LRI					0.6769					

Note: *, **, and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 3b. Coefficient Estimates for the Standard Multinomial Logit Model of Land-use Change on Forestland, 1995-2000

Indep. Variable	Farmland		Grassland		Water area		Urban area		Unused land	
	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Intercept	-3.1282***	(0.2178)	-2.8665***	(0.1752)	-4.8250***	(0.7760)	-6.0391	(4.1793)	-3.9343***	(0.7437)
Land productivity	0.0990***	(0.0117)	0.0545***	(0.0171)	0.0116	(0.0441)	0.0249	(0.1358)	0.1021	(0.0832)
County GDP	-0.0041	(0.0067)	0.0150	(0.0092)	-0.0010	(0.0491)	-0.0115	(0.0348)	-0.1897	(0.2619)
Population	-0.0752	(0.0822)	-0.1991*	(0.1049)	0.2150	(0.4086)	-0.4762	(1.3089)	0.6480	(0.9809)
Agricultural investment	0.1755**	(0.0827)	0.1137	(0.0966)	0.2246	(1.0142)	0.3394	(4.7189)	-2.1817**	(1.1069)
Highway density	0.0393	(0.0459)	0.0786	(0.0605)	0.0395	(0.2035)	-0.2168	(0.5256)	-0.8677*	(0.4527)
Terrain slope	-0.0391***	(0.0077)	-0.0175***	(0.0063)	-0.1895***	(0.0505)	-0.1908	(0.1509)	-0.1638***	(0.0411)
Elevation	-0.2066***	(0.0483)	0.1420***	(0.0328)	-1.2181***	(0.1924)	-0.4573	(0.6115)	0.3046*	(0.1579)
Precipitation	-0.4585***	(0.1338)	-1.1202***	(0.1378)	-0.6447	(0.5126)	-1.6371	(1.8932)	-4.4378***	(0.7968)
Temperature	0.0480***	(0.0085)	0.0391***	(0.0069)	0.0831***	(0.0300)	0.1561	(0.1177)	0.0179	(0.0293)
Std Err of precipitation	-1.1567**	(0.5049)	0.0428	(0.6458)	-2.6334	(1.9783)	-0.9844	(6.5859)	0.1497	(3.0380)
Std Err of temperature	1.0541***	(0.3198)	0.7215***	(0.2633)	1.3924	(1.1542)	-0.4434	(4.5842)	2.6569**	(1.1504)
Neighborhood index	0.0411***	(0.0012)	0.0387***	(0.0012)	0.0813***	(0.0064)	0.1319***	(0.0160)	0.0536***	(0.0050)
Number of observations					19488					
McFadden's LRI					0.6771					

Note: *, **, and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 4a. Coefficient Estimates for the Standard Multinomial Logit Model of Land-use Change on Grassland, 1988-1995

Indep. Variable	Farmland		Forestland		Water area		Urban area		Unused land	
	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Intercept	-2.5272***	(0.2438)	-3.2139***	(0.2120)	-4.5855***	(0.4887)	-8.1604***	(2.9041)	-2.4478***	(0.2899)
Land productivity	0.0782***	(0.0171)	0.1272***	(0.0197)	0.1898***	(0.0508)	0.3214*	(0.1786)	-0.1199**	(0.0549)
County GDP	0.0527**	(0.0250)	-0.0053	(0.0366)	0.1095*	(0.0574)	0.0575	(0.6718)	0.1456***	(0.0426)
Population	0.4507***	(0.1550)	0.8189***	(0.1669)	0.0486	(0.5327)	-0.8714	(3.6464)	-0.5820	(0.4588)
Agricultural investment	-0.1943	(0.1893)	0.3088**	(0.1298)	0.4021	(0.4338)	-0.1310	(4.6872)	-1.1709***	(0.3279)
Highway density	0.1609***	(0.0428)	0.0957	(0.0642)	0.1711	(0.1471)	-0.4573	(0.7783)	0.0610	(0.0844)
Terrain slope	0.0140	(0.0095)	0.0380***	(0.0069)	-0.0609***	(0.0228)	-0.0157	(0.1109)	-0.0324***	(0.0083)
Elevation	-0.4717***	(0.0510)	-0.1437***	(0.0335)	-0.1110	(0.0848)	0.5892	(0.7513)	0.0267	(0.0481)
Precipitation	0.5282**	(0.2319)	0.7794***	(0.2024)	0.5972	(0.6803)	-0.9467	(3.8030)	-1.1148***	(0.4158)
Temperature	-0.0039	(0.0105)	-0.0163**	(0.0080)	-0.0669***	(0.0221)	0.2157	(0.2476)	-0.0166	(0.0112)
Std Err of precipitation	0.5156	(1.0097)	-1.3059	(0.8522)	1.2753	(2.7736)	-0.2273	(20.728)	1.5814	(2.4712)
Std Err of temperature	-1.0408**	(0.4464)	-0.8175**	(0.4057)	-0.6959	(0.9127)	-3.7185	(8.2997)	-1.3545***	(0.4911)
Neighborhood index	0.0556***	(0.0015)	0.0583***	(0.0013)	0.0997***	(0.0038)	0.1662***	(0.0339)	0.0559***	(0.0013)
Number of observations					17893					
McFadden's LRI					0.6611					

Note: *, **, and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 4b. Coefficient Estimates for the Standard Multinomial Logit Model of Land-use Change on Grassland, 1995-2000

Indep. Variable	Farmland		Forestland		Water area		Urban area		Unused land	
	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Intercept	-3.1325***	(0.2143)	-3.4663***	(0.1859)	-5.7489***	(0.7341)	-5.0566	(9.2609)	-3.8559***	(0.2912)
Land productivity	0.1507***	(0.0147)	0.0755***	(0.0183)	0.2003***	(0.0652)	0.1022	(0.7749)	-0.0911**	(0.0425)
County GDP	-0.0741***	(0.0170)	-0.0139	(0.0153)	0.0166	(0.0731)	-0.1279	(0.7389)	0.1583***	(0.0175)
Population	0.6967***	(0.1522)	0.7112***	(0.1441)	0.3270	(0.8176)	-0.7448	(10.550)	-1.8065***	(0.3724)
Agricultural investment	0.2416**	(0.1163)	-0.1530	(0.1156)	0.0391	(0.8088)	-0.3704	(31.015)	-1.4602***	(0.2927)
Highway density	0.2093***	(0.0612)	0.1865***	(0.0625)	0.1130	(0.1575)	0.6222	(0.5172)	-0.7420***	(0.0853)
Terrain slope	0.0051	(0.0099)	0.0459***	(0.0063)	-0.0908***	(0.0240)	-0.1523	(0.6673)	-0.0359***	(0.0080)
Elevation	-0.3827***	(0.0568)	-0.1004***	(0.0341)	0.2322	(0.1546)	-2.2314	(8.8000)	0.3706***	(0.0561)
Precipitation	-0.0689	(0.1657)	0.0342	(0.1496)	-0.1111	(0.8861)	0.0435	(13.290)	-2.4384***	(0.3838)
Temperature	0.0363***	(0.0094)	-0.0001	(0.0073)	-0.0044	(0.0313)	0.0735	(0.6435)	0.1005***	(0.0121)
Std Err of precipitation	-0.3487	(0.9213)	3.1369***	(0.7336)	0.5856	(4.7753)	0.1013	(65.121)	0.1737	(1.93550
Std Err of temperature	0.1826	(0.2723)	-0.0810	(0.2547)	0.5449	(0.7414)	-1.6131	(12.739)	1.9762***	(0.3033)
Neighborhood index	0.0435***	(0.0015)	0.0398***	(0.0012)	0.0819***	(0.0047)	0.0927	(0.1070)	0.0287***	(0.0012)
Number of observations					18116					
McFadden's LRI					0.6157					

Note: *, **, and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

Table 5a. Description of Simulation Scenarios

Scenario	Description
Factual	All variables at actual values
No change in mean precipitation	Fix the mean annual *precipitation* at the average values of 1991-95
No change in mean temperature	Fix the mean annual *temperature* at the average values of 1991-95
No variation around mean precipitation	Restrict the coefficients of the standard deviations of *precipitation* to be zero
No variation around mean temperature	Restrict the coefficients of the standard deviations of *temperature* to be zero

Table 5b. Simulated Changes in Land Supplies of Six Major Uses, 1988-2000a

Change in major land use		Factual	No change in mean precipitation	No change in mean temperature	No variation around mean precipitation	No variation around mean temperature
Farmland	(1,000 ha.)	1274.5	1687.4	1017.4	4249.3	482.6
	%	0.0%	-32.4%	20.2%	-233.4%	62.1%
Forestland	(1,000 ha.)	-649.9	-1108.1	-244.3	-5445.6	11445.0
	%	0.0%	70.5%	-62.4%	737.9%	-1861.0%
Grassland	(1,000 ha.)	-2320.2	-2100.3	-1706.2	-3233.9	-13371.1
	%	0.0%	-9.5%	-26.5%	39.4%	476.3%
Water area	(1,000 ha.)	-217.1	-226.9	-152.0	-67.4	-4377.0
	%	0.0%	4.5%	-30.0%	-68.9%	1915.7%
Urban area	(1,000 ha.)	2526.7	2533.4	2508.0	2723.8	4321.8
	%	0.0%	-0.3%	0.7%	-7.8%	-71.0%
Unused land	(1,000 ha.)	-613.8	-785.5	-1422.9	1773.9	1498.6
	%	0.0%	28.0%	131.8%	-389.0%	-344.1%

[a] Change in hectare is the total land area change for each use between 1988 and 2000. Percent change is the net hectare change under each counterfactual scenario relative to the hectare change under factual scenario. Positive (negative) values indicate that the factor contributes to increasing (decreasing) the land hectare for that use.

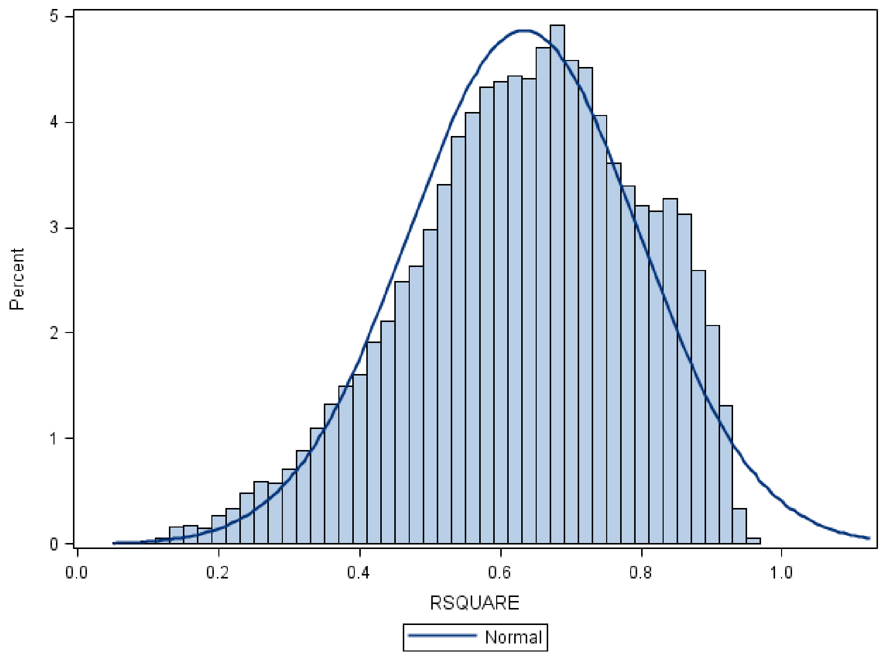

Figure 1. Histogram of the pooled R-square for SOC density model.

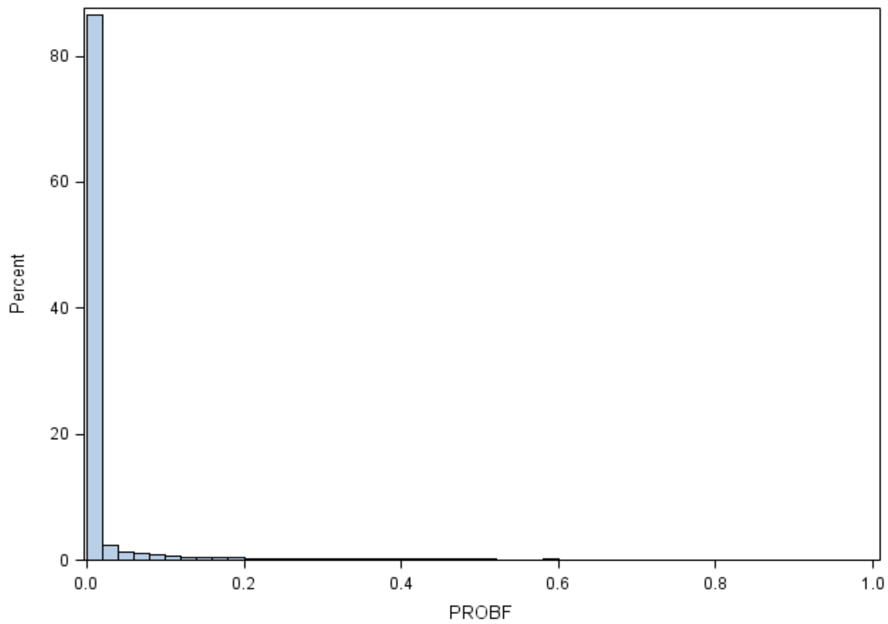

Figure 2. Histogram of the pooled P-value of land-use dummy variable in SOC density model.

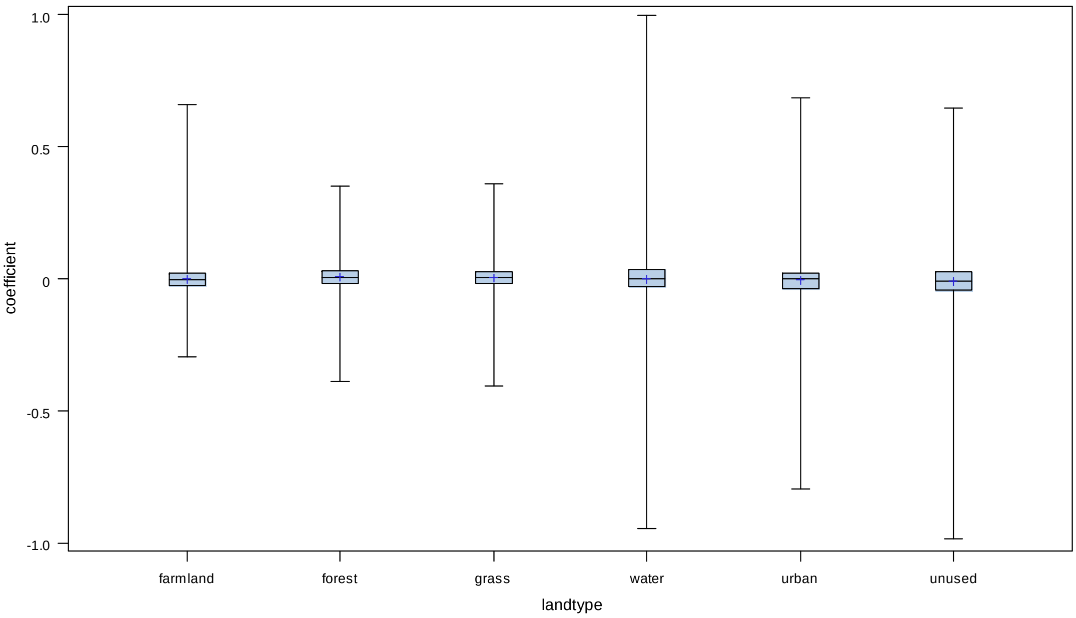

Figure 3. Boxplots of coefficient estimates of land-use dummy variable in SOC density model.

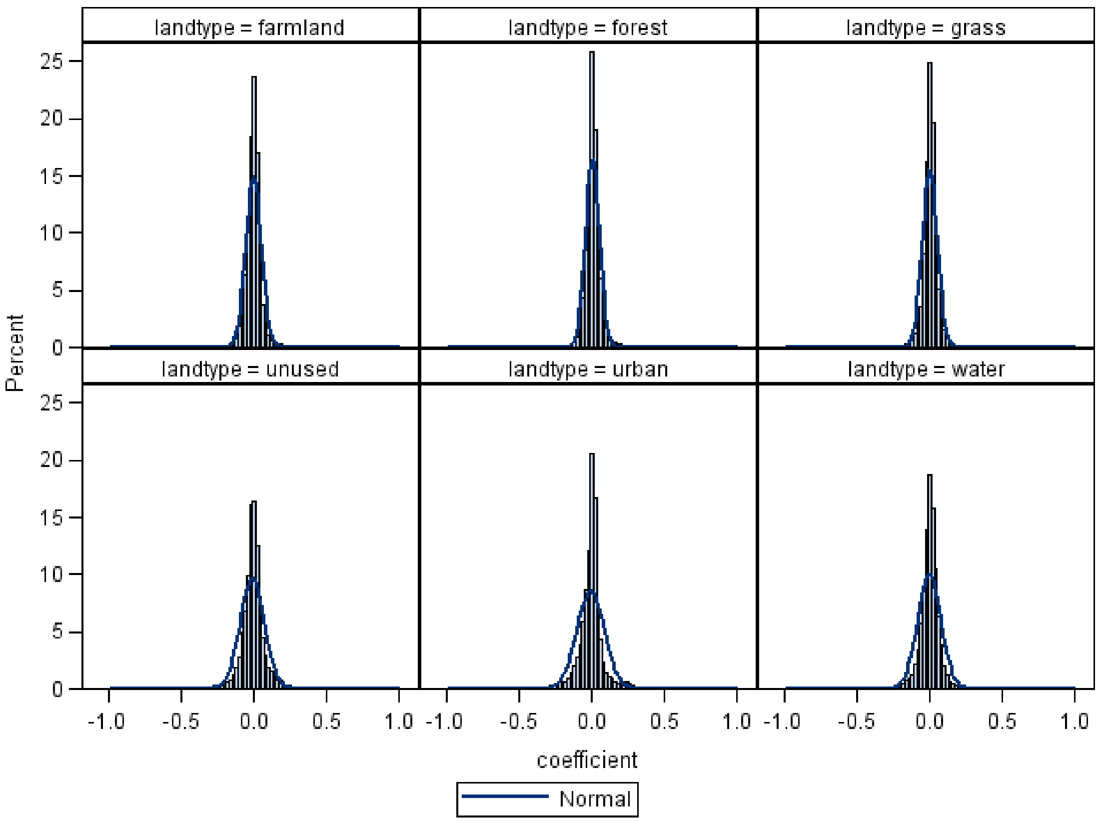

Figure 4. Histogram panel of coefficient estimates of land-use dummy variable in SOC density model.

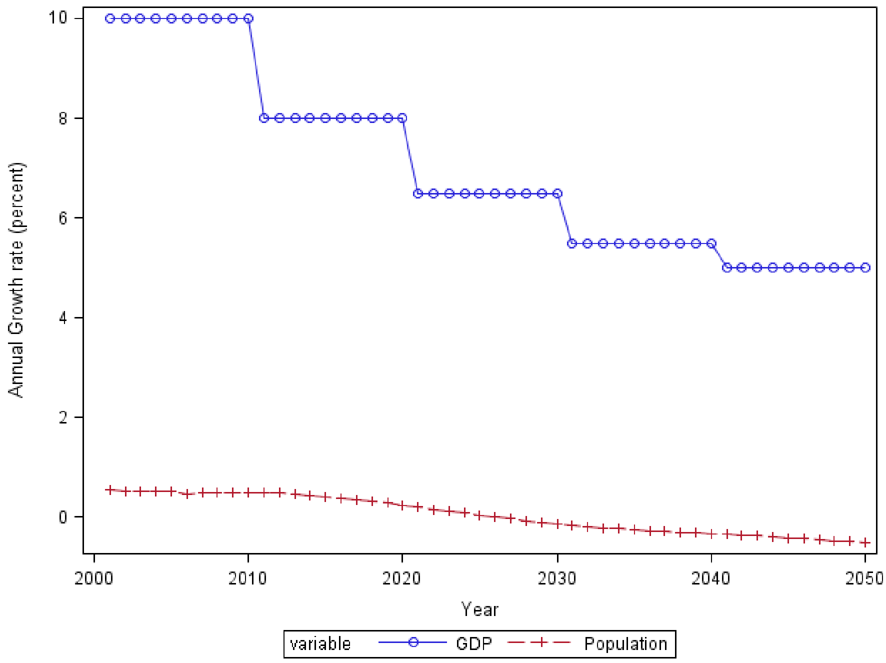

Figure 5. Annual growth rate of GDP and population in the baseline scenario.

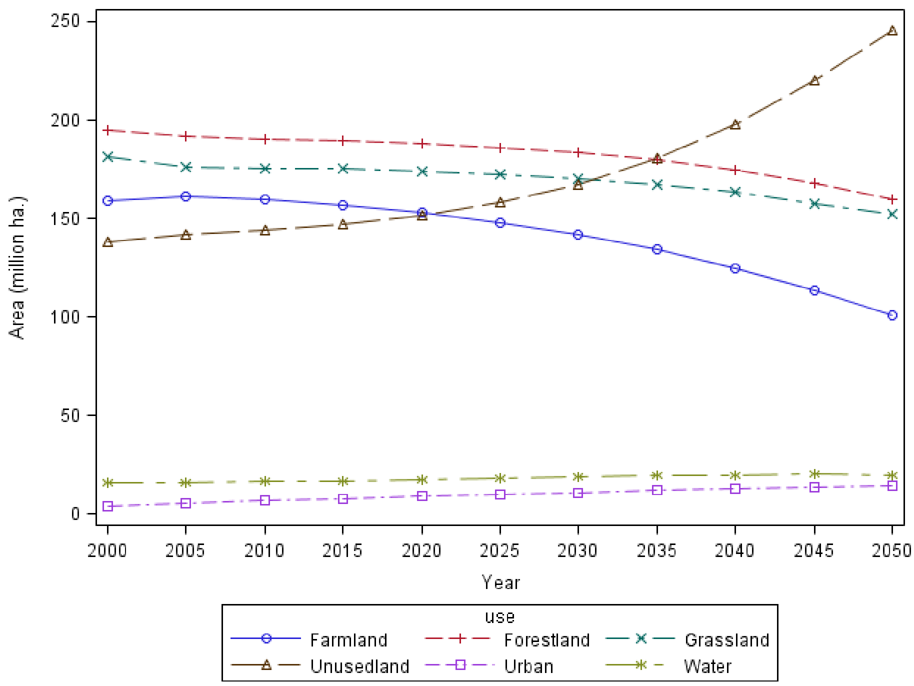

Figure 6. The area of land by use in the baseline scenario.

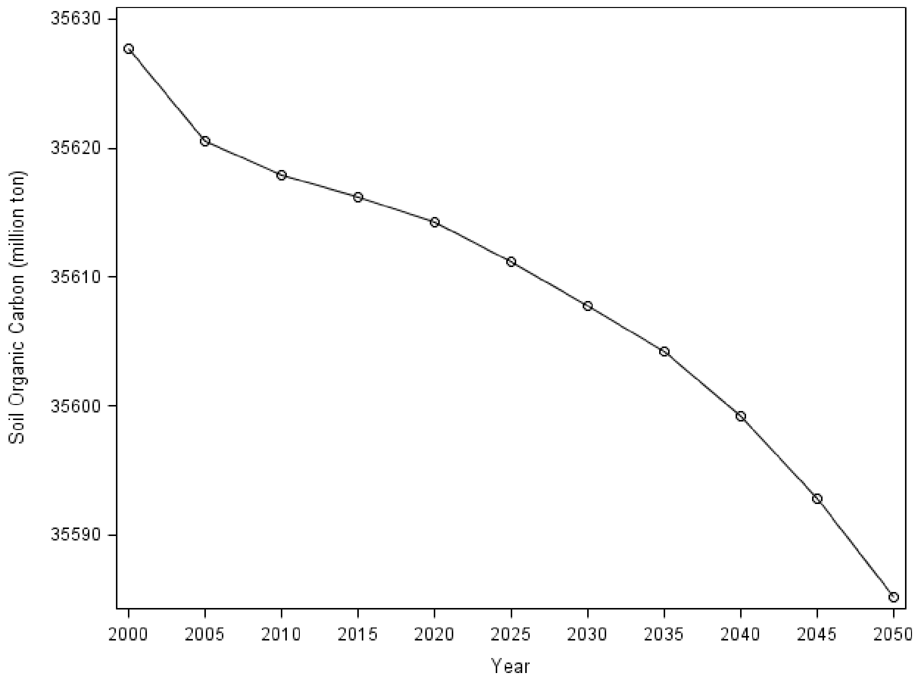

Figure 7. The amount of soil organic carbon in the baseline scenario.