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Unintended Effects of Urbanization in China

Land Use Spillovers and Soil Carbon Loss

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ABSTRACT

This paper uses a national-level geographic information system database on land use, weather conditions, land quality, soil organic carbon (SOC), topographic features, and economic variables to analyze the major drivers of land use change and the resulting impact on soil carbon storage in China. The framework developed in this study includes two main components. One is a spatial panel multinomial logit land use model that takes into account the spatial and temporal dependence of land use choices explicitly. The other is a statistical causal evaluation model that estimates the effect of land use change on SOC density. Results indicate that local economic growth, as measured by county-level gross domestic product, was a major cause of urban development and grassland conversions. Rapid expansion of road networks, promoted by massive public investment, increased the conversion of forests, grassland, and unused land to crop production and urban development. Urbanization had significant secondary ripple effects in terms of both indirect land use change and soil carbon loss. Some of the soil carbon loss may be irreversible, at least in the short run.

Keywords: China, road density, land use, soil organic carbon, spatial panel, propensity score–matching

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1. INTRODUCTION

China has experienced rapid urbanization during the last 20 years. From 1988 to 2005, the total developed area increased by 3.3 million hectares. The fraction of population residing in urban areas increased from 26 percent to 46 percent during the period 1990–2008 (CASS 2009). The total length of China's roads doubled from 2005 to 2010. This rapid urbanization has led to dramatic land use changes in many parts of the country. These land use changes have major economic, environmental, and social consequences. For example, rapid conversion of high-quality farmland to development in traditional agricultural regions such as Huang-Huai-Hai Plain, Yangtze River Delta, and Sichuan Basin is believed by many to be a major threat to China's national food security. This concern is rooted in the fact that China is home to one-fifth of the world's population (World Bank 2010) but only 10 percent of world's cultivatable cropland (FAO 2008). The Chinese government established the Basic Farmland Protection Regulation (China, State Council 1994) and revised the Land Administration Law in 1998 (China, Standing Committee 1998) to try to slow down the pace of farmland conversion, but hundreds of thousands of acres of high-quality farmland are still being converted to development each year, particularly in rapidly urbanizing regions.

Urbanization has many secondary ripple effects. As farmland is converted to development in coastal regions, total crop production will decrease and agricultural commodity prices will increase. This, together with government subsidies for crop production and market schemes, will provide farmers in other regions with incentives to increase crop production by converting forests and grassland to cropland. In close conjunction with urbanization, China has made a tremendous amount of public investment in transportation infrastructure during the last 20 years. During the period 1988–2009, China invested approximately US$40 billion per year to upgrade its road system. This massive public investment has led to an increase in the total road length by 2.9 million kilometers, which is almost a threefold increase compared with the road length of 1 million kilometers in 1988 (NBSC 2001–2010, 2005). This road network, the second longest after only the U.S. interstate highway system, is designed to eventually connect all cities of more than 200,000 people (World Bank 2007). Building roads through, near, or to forests and grassland may improve the economic viability in the area, but it may also encourage encroachment of farmland into forest and grass areas.

Consequently, despite the loss of high-quality farmland in traditional agricultural regions, the total acreage of farmland in China increased by 2.6 million hectares from 1988 to 2005, due largely to the conversion of grass and forest lands to crop production.[1] China had 303 million hectares of grassland in 1988, accounting for approximately one-third of the total national land area. By 2005, the total acreage of grassland had reduced to about 291 million hectares, a 3.9 percent reduction. Most of the reduction occurred in farming-pasture zones of eastern Inner Mongolia, North China Plain, and Loess plateau (Liu et al. 2003).

The conversion of grassland to crop production could have a dramatic effect on total soil carbon storage. A previous study showed that the soil organic carbon (SOC) density of grassland has decreased by 3–10 kilogram carbon (kgC) /m^2 in the western grassland region and by 10–20 kgC/m^2 in the southeast region of the Tibet Plateau since the 1960s (Wang et al. 2003). Currently, the rates of grassland conversions are still low relative to the rates of farmland conversions experienced in coastal regions of China. However, as rapid economic development reaches interior regions,[2] more land conversions will occur in those regions. A comprehensive analysis of land use changes in China and their environmental effects will provide important information for the design of land use and conservation policies in China.

[1] The total forest acreage increased by 1 million hectares during this period, partly due to grassland conversion to forests and partly due to policy interventions. In 1999, the Chinese government launched a nationwide cropland set-aside program known as Grain for Green to increase forest cover and reduce China's long practice of cultivation on steep slopes.

[2] Two reasons for the potential trend of economic development in interior regions are as follows: (1) Western development is one of the guidelines for Chinese policymakers. (2) Increasing land rent and labor costs in coastal provinces increases the burden of many small manufacturers. Some of them have moved to interior regions.

This paper presents an empirical model to quantify the effects of major socioeconomic drivers on land use change and the resulting impact on soil carbon storage in China. Of particular interest is road network development. For this purpose, this study compiles two datasets from a high-quality national geographic information system (GIS) database provided by the Chinese Academy of Sciences (CAS). The first one includes land use data for four years (1988, 1995, 2000, 2005), which was originally generated from Landsat Thematic Mapper scenes with a spatial resolution of 30×30 m^2. Landsat images and land cover classifications were interpreted by CAS, and the average interpretative accuracy is more than 97 percent (Deng 2011). The second dataset includes cross-sectional soil profile data in the mid-1980s, which were initially collected by a special nationwide research and documentation project (the Second National Soil Survey of China) organized by the State Council and carried out by a consortium of universities, research institutes, and soils extension centers. CAS interpolated the information into surface data using the Kriging algorithm (Burgess and Webster 1980) to get more disaggregated information for each pixel.

We developed two models using these rich datasets. The first one is a spatial econometric land use model, which takes into account potential econometric problems resulting from spatial panel data, such as spatial heterogeneity, spatial dependence, and temporal heteroskedasticity. In particular, this study adopts a new method proposed by Li, Wu, and Deng (2011) to explicitly model spatial and temporal dependence in a multinomial logit model. The method is computationally feasible even with a large dataset. The second model is a statistical causal evaluation model to assess the effect of land use change on SOC density, which we refer to as the SOC model. This approach can be applied to a large region and hence overcomes the limitation of a process model that typically works only for a field-level study. In addition, we employ the propensity score–matching method to eliminate the potential bias from self-selection on land use choices. The self-selection may result from nonrandomized initial land uses (that is, the control) in an observational study. Combining the land use and SOC models, we analyze the effect of rapid road network development on land use and soil carbon content in China.

The remainder of this paper is organized as follows: Section 2 develops the land use model. Section 3 develops the SOC model. Section 4 discusses road network development and SOC loss. The final section offers our conclusions.

2. THE SPATIAL PANEL MULTINOMIAL LOGIT LAND USE MODEL

To model land use change in China, one must fully understand China's landownership. Unlike the United States and many European countries, China has no private land; land is owned either by the state or by a village collective, depending on land use types. For example, all urban land and most forests, pasture, water areas, and unused land belong to the state; all farmland is collectively owned by villagers. The government also heavily regulates land use. The state retains the right to requisition farmland and other collectively owned land for urban and industrial development and other purposes by compensating villagers based on the original use of the land. Land requisition is a unique type of landownership transaction in China.[3]

Empirical Specification

Land use decisions are made by two types of agents in China—government officials (county level or above) and village collectives. These two types of agents have different objectives when making land use decisions. Government officials usually seek to maximize their *political achievements*, which are often measured by the level and growth of local gross domestic product (GDP) and shown off by large *image projects* such as big boulevards and central squares. In addition to family backgrounds and political connections, the most important factor affecting promotion opportunities for a government official is these so-called political achievements. In contrast, village collectives seek to maximize net benefits from land use. The key variables affecting the net benefits from alternative land uses include geophysical variables such as land quality, topography, and weather conditions, and the level of economic development and human activity as measured by local GDP and population. It would be desirable to include these net benefits when modeling village collectives' land use decisions, but such data are unavailable. Therefore, local GDP, population, and weather and land quality are hypothesized to affect net benefits from alternative land use.

Consider land use choice within a 10 × 10 km land grid, indexed by n; $n = 1,\ldots, N$. Let U_{intj} denote the agent's utility from allocating land parcel i to use j at time t; $i = 1,\ldots, I$; $j = 1,\ldots, J$; and $t = 1,\ldots, T$. Our data identify the proportions of six alternative uses—farmland, forests, grassland, water area, urban land, and unused land—within each land grid but do not provide information about individual parcels within a grid. Thus, we decompose U_{intj} into a deterministic component and an unobserved random component:

$$U_{intj} = \mathbf{X}_{nt}\boldsymbol{\beta}_j + \varepsilon_{intj} . \tag{1}$$

Based on the economic theories and previous studies (Deng et al. 2008; Fujita 1989; Hall 1966), the deterministic component $\mathbf{X}_{nt}\boldsymbol{\beta}_j$ is specified as

$$\mathbf{X}_{nt}\boldsymbol{\beta}_j = \mathbf{d}_{nt-1}\boldsymbol{\beta}_j^d + \mathbf{y}_{nt}\boldsymbol{\beta}_j^y + \mathbf{z}_{ct}\boldsymbol{\beta}_j^z , \tag{2}$$

where $\mathbf{d}_{nt-1}$ represents a vector of land use proportion in grid n at time t–1, which together with other variables captures conversion costs; $\mathbf{y}_{nt}$ is a vector of variables describing land quality, topography, and weather conditions of grid n at time t; $\mathbf{z}_{ct}$ is a set of socioeconomic variables in county c where the parcel is located; and $\boldsymbol{\beta}_j^d$, $\boldsymbol{\beta}_j^y$, and $\boldsymbol{\beta}_j^z$ are vectors of coefficients on $\mathbf{d}_{nt-1}$, $\mathbf{y}_{nt}$, and $\mathbf{z}_{ct}$, respectively. At the national scale, socioeconomic data are available only at the county level or higher. ε_{intj} is the random component representing the attributes of parcel i or the characteristics of the person making land use decisions, which are unobservable by the researcher but affect the agent's utility.

[3] China's land market is generally referred to as *land use right market*, which emerged since the amended constitution legalized land use right transactions in 1988. The constitution specifies both conveyance and transfer markets of land use right, where conveyance market is a primary land market in which transactions occur between government and land users, and transfer market is a secondary land market in which transactions occur between land users.

If the unobserved random component ε_{intj} is assumed to follow an independent identical type-I extreme value distribution, the probability of any land parcel within grid n allocated to use j at time t can be derived as follows (Train 2003):

$$P_{ntj} = \Pr\left(U_{intj} > U_{intl}, \forall\, j \neq l\right) = \frac{e^{\mathbf{X}_{nt}\boldsymbol{\beta}_j}}{\sum_l e^{\mathbf{X}_{nt}\boldsymbol{\beta}_l}}. \tag{3}$$

Equation (3) is estimated using the maximum likelihood method. The log-likelihood function with proportion data is $LL = \sum_t \sum_n \sum_j d_{ntj} \ln P_{ntj}$, where d_{ntj} is the jth entry of the vector $\mathbf{d}_{nt}$, representing the share of land use j in grid n at time t. To avoid redundant parameters, we set the unused land J as reference and normalize $\boldsymbol{\beta}_J = \mathbf{0}$. Then the coefficient vector $\boldsymbol{\beta}_j$ in model (3) reflects associations between explanatory variables ($\mathbf{X}_{nt}$) and the log odds $\log(\frac{P_{ntj}}{P_{ntJ}})$. The marginal effects of explanatory variables on the probability of grid n being converted to use j at time t can be derived as

$$\frac{\partial P_{ntj}}{\partial \mathbf{X}_{nt}} = P_{ntj}\left(\boldsymbol{\beta}_j - \sum_l P_{ntl}\boldsymbol{\beta}_l\right). \tag{4}$$

Econometric Issues and Estimation Methods

Spatial dependence and spatial heterogeneity (nonstationarity) are important econometric concerns when applying contiguous geographic data for empirical analysis. In a multinomial logit model, the cost of not correcting for spatial dependence or heterogeneity is biased (or inconsistent) estimates if these spatial issues induce heteroskedastic errors (Yatchew and Griliches 1985).[4] Testing for spatial heterogeneity is as straightforward as tackling cross-sectional heterogeneity (Anselin 2006). However, in the context of the discrete dependent variable model, the econometric theory of testing for spatial lag dependence is still in its infancy. In the time domain, modeling repeated land use choices poses another challenge. If temporal heteroskedasticity is present and an independent identical distribution (i.i.d.) random error is incorrectly assumed, maximum likelihood estimators will be biased. Furthermore, the lagged value $\mathbf{d}_{nt-1}$ in the right side of equation (2) at time t contains information that will appear in its left side at time t–1, leading to biased maximum likelihood estimators.

To correct for the potential econometric problems discussed above, we develop a spatial panel multinomial logit model that explicitly takes into account the spatial and temporal dependence of land use choices (see Li, Wu, and Deng 2011 for more detailed discussions on the methodology). Formally, suppressing the land use subscript j, spatial dependency is modeled in a stacked form,

$$\mathbf{U}_t = \rho_t \mathbf{W}\mathbf{U}_t + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t, \tag{5}$$

where ρ_t is a spatial autoregressive parameter ($|\rho_t| < 1$). The magnitude of ρ_t represents the extent to which an element of the left-side variable U_{nt} is affected by the remaining elements U_{mt} for $m \neq n$. We assume $\mathbf{W}$ is a row-standardized $N \times N$ first-order queen contiguity weight matrix, that is, $\sum_{m=1}^{N} w_{nm} = 1$, $w_{nm} > 0$ if grids n and m share common borders and vertexes, and $w_{nm} = 0$ otherwise. This assumption maintains the essential structure of a standard spatial model while facilitating the estimation of marginal effects as addressed below. The reduced form of equation (5) is $\mathbf{U}_t = \left(\mathbf{I}_N - \rho_t\mathbf{W}\right)^{-1}\mathbf{X}_t\boldsymbol{\beta} + \left(\mathbf{I}_N - \rho_t\mathbf{W}\right)^{-1}\boldsymbol{\varepsilon}_t$.

[4] The standard logit formula is derived from the assumption that the unobserved error follows a type I extreme value distribution with variance $\pi^2/6$, which is equivalent to normalizing the model by a scale parameter s if the unobserved factor has the variance $(\pi^2/6)\sigma^2$. Hence, each of real coefficients $\boldsymbol{\beta}$ is scaled by $1/\sigma$. $\boldsymbol{\beta}$ and σ are not separately identified; only the ratio $\boldsymbol{\beta}/\sigma$ can be estimated. See Train (2003) for a detailed discussion.

The temporal variance–covariance matrix of the unobserved random error between periods t and s takes the general form $E\left(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_s{}'\right) = \omega_{ts}\left[\left(\mathbf{I}_N - \rho_s \mathbf{W}\right)'\left(\mathbf{I}_N - \rho_t \mathbf{W}\right)\right], \forall\ t, s$, where $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\varepsilon}_s$ are N-dimensional vectors, ω_{ts} is a temporal covariance between t and s, and $\mathbf{I}_N$ is an N-dimensional identity matrix. Let $\sigma_{nt}{}^2$ be the diagonal elements of matrix $\left[\left(\mathbf{I}_N - \rho_s \mathbf{W}\right)'\left(\mathbf{I}_N - \rho_t \mathbf{W}\right)\right]^{-1}$; then the error variance is reduced to $\omega_{tt}\sigma_{nt}{}^2$. For notational convenience, let $\mathbf{X}_{nt}^* = \mathbf{X}_{nt}\omega_{tt}^{-1/2}\sigma_{nt}^{-1}$ and $\mathbf{X}_t^{**} = \left(\mathbf{I}_N - \rho_t \mathbf{W}\right)^{-1}\mathbf{X}_t^*$. Now the expression of the probability of grid n being converted from land use k to land use j at time t is

$$P_{ntj} = \frac{e^{\mathbf{X}_{nt}^{**}\boldsymbol{\beta}_j}}{\sum_l e^{\mathbf{X}_{nt}^{**}\boldsymbol{\beta}_l}}. \tag{6}$$

To overcome the endogeneity problem caused by the specification of the time-lagged proportion, land use in 1988 is treated as the *initial land use* when modeling land use transition for all three periods: 1988–1995, 1995–2000, and 2000–2005. The endogeneity problem is avoided because the dependent variable reflects land use decisions only at the end of each transition period (1995, 2000, and 2005).

When N is large, it is infeasible to estimate model (6) using a traditional method based on log-likelihood function because the likelihood function involves an NT-dimensional integration. This study adopts the linearized generalized method of moments (GMM) approach suggested by Li, Wu, and Deng (2011) to estimate the spatial panel multinomial logit model. Appendix A provides a detailed discussion on the procedure. It is easy to estimate the marginal effects of the transformed variables $\mathbf{X}_{nt}^{**}$ using formula (4). However, it makes more sense to know the marginal effects of the observed $\mathbf{X}_{nt}$ on land use probability. Hence, we need to modify formula (4) by accounting for the scale parameter $\omega_{tt}{}^{1/2}\sigma_{nt}$ and the diagonal elements of matrix $\left(\mathbf{I}_N - \rho_t \mathbf{W}\right)^{-1}$. Equation (7) gives the revised formula for estimating the marginal effects:

$$\frac{\partial P_{ntj}}{\partial \mathbf{X}_{nt}} = \frac{\left[\left(\mathbf{I}_N - \rho_t \mathbf{W}\right)^{-1}\right]_{nn}}{\sqrt{\omega_{tt}}\,\sigma_{nt}} P_{ntj}\left(\boldsymbol{\beta}_j - \sum_l P_{ntl}\boldsymbol{\beta}_l\right). \tag{7}$$

Data

Our study covers the whole of mainland China. Most data used in this paper were provided by the Chinese Academy of Sciences (CAS), including land uses, topography, climate, and socioeconomic data. A land grid is 10 × 10 km.

CAS generated the contiguous land use data based on the U.S. Landsat Thematic Mapper/Enhanced Thematic Mapper (TM/ETM) images (Deng et al. 2006, 2008). The data are available for four time periods—the late 1980s, the mid-1990s, the late 1990s, and the middle years of the 2000–2010 decade—denoted as 1988, 1995, 2000, and 2005, respectively. CAS made visual interpretations and digitization of TM/ETM images to generate thematic maps of land uses and sorted the data with a hierarchical classification system of 25 land use classes, which were then further grouped into six aggregated classes: farmland, forests, grassland, water area, urban land, and unused land. In particular, water area is classified as land covered by natural water bodies and land with facilities for irrigation and water conservation; urban land includes land used for urban and rural settlements, industry, and transportation. Deng et al. (2006) provides a detailed explanation of the six aggregated land use classes.

Table 2.1 depicts land use conversions among these classes for 1988–2005, where the row represents initial use and the column represents final use.[5] Land use changes occurred mainly between farmland, forests, and grassland, and between grassland and unused land. All land uses except grassland increased. Specially, urban area expanded by 56 percent, the largest change among the six classes. Farmland development accounts for 80 percent of that expansion.

Table2.1—Remotely sensed land use conversions in China, 1988-2005

		Final land use						
Initial land use		Farm	Forest	Grass	Water	Urban	Unused	Total
Farm	Frequency	16,896	341	346	105	281	60	18,029
	Percent	0.937	0.019	0.019	0.006	0.016	0.003	1
Forest	Frequency	524	22,547	481	18	32	91	23,693
	Percent	0.022	0.952	0.020	0.001	0.001	0.004	1
Grass	Frequency	745	849	27,760	50	26	1,033	30,463
	Percent	0.024	0.028	0.911	0.002	0.001	0.034	1
Water	Frequency	75	15	53	2,042	20	91	2,296
	Percent	0.033	0.007	0.023	0.889	0.009	0.040	1
Urban	Frequency	46	7	8	16	444	3	524
	Percent	0.088	0.013	0.015	0.031	0.847	0.006	1
Unused	Frequency	184	59	567	103	16	18,976	19,905
	Percent	0.009	0.003	0.028	0.005	0.001	0.953	1
Total		18,470	23,818	29,215	2,334	819	20,254	94,910

Source: Chinese Academy of Sciences' remote sensing database.

Data on geophysical variables were generated from a geographic information system (GIS) database, including time-invariant data of land quality, terrain slope, and elevation. Land quality is an index of potential crop yield, originally measured at a 5 km pixel level. A research team from CAS, using the stand-alone software of Estimation System for Land Productivity, estimated the yield potential (Deng 2011). Terrain slope and elevation are generated from China's digital elevation model as part of the basic CAS database. Climate panel data are initially collected from more than 600 weather stations and organized by the China Administration. The dataset includes annual precipitation and mean annual temperature from 1991 to 2005; CAS interpolated the point climate data into surface data with the method of thin-plate smoothing spline to get more disaggregated information for each pixel. We calculate the averages and standard deviations of annual precipitation and mean annual temperature for each conversion period. The standard deviations measure temporal variations in weather. We assume that these estimated means and standard derivations are constant through every short transition period (1988–1995, 1995–2000, and 2000–2005).

Based on a digital map of transportation networks in the mid-1990s, road density is calculated as the total length of all highways, national expressways, provincial-level roads, and other minor roads in a county divided by the land area of that county. County road density is available only for the mid-1990s. As a supplement, we collected provincial road length for four years (1988, 1995, 2000, and 2005) to calculate the province-level growth rate of road length. Lacking better data, we use the county road density in 1995 and the provincial growth rate to extrapolate the road density in 1988, 2000, and 2005 for each county. Data on county GDP and population for 1989, 1996, 2000, and 2005 are gathered from several versions of statistical and population yearbooks. Because we could not determine exactly when land use changes occurred during a time interval, we use the 1988–1989, 1996, and 2000 data to control

[5] In Table 2.1, we assign each grid to a use based on the land proportion within the grid; the use with the highest predicted proportion is assigned to the grid. We use grid-level land proportions in the estimation. Generally, urban area will not be converted to nonurban uses. In this study, however, urban land includes land used for rural settlements, which can be converted to agricultural use.

for the initial land use for the three respective transition periods. The lagged measures help to reduce endogeneity. We use the 2005 data as a baseline for policy simulation. Data on public agricultural investment are collected from province- and county-level statistical yearbooks and are available for four years (1994, 1995, 1999, and 2000). The investments came from state and local governments and were used mainly for developing agriculture infrastructure such as seeds, fertilizers, and irrigation projects. We use public agricultural investments in 1994, the average of public agricultural investments in 1995 and 1999, and public agricultural investments in 2000 when explaining land use change during the three periods (1988–1995, 1995–2000, and 2000–2005), respectively. Data on public agricultural investment are not available for 2005. Based on the value in 2000, we use the county-level growth rate between 1995 and 2000 to extrapolate the investment in 2005. All value variables are measured at the 2000 real Chinese yuan.

After adjusting for missing data, the panel dataset that is used for the empirical analysis contains 68,918 observations for each period. Table B.1 in Appendix B provides some summary statistics for the variables used in this analysis.

Results

We perform a likelihood ratio test to examine the homogeneity of variance in the time domain. The test rejects the null at the 1 percent level, implying that the error variance demonstrates temporal heteroskedasticity. The error variance for the first period (1988–1995) is estimated to be 10 percent larger than the variance for the second period (1995–2000) and 1.6 percent smaller than the variance for the third period (2000–2005). We also conduct a lack-of-fit F-test to assess the temporal stability of the spatial autoregressive parameter (the null hypothesis is $\rho_1 = \rho_2 = \rho_3$). The test fails to reject the null at the 10 percent level. Hence, we estimated the spatial panel multinomial logit model by assuming $\rho_1 = \rho_2 = \rho_3$. There is convincing evidence that land uses in neighboring parcels directly affect each other (two-sided p-value $<< 0.01$, degree of freedom = 1,033,684). In particular, ρ is estimated to be 0.0295, indicating the presence of strongly positive spatial interdependencies, implying that neighboring land grids tend to be similar in land use.

In a GMM regression, R^2 does not have a statistical interpretation. Therefore, we evaluate the performance of the spatial panel model by its prediction accuracy (see Table B.2). First, we assign each grid a use based on the predicted probability; the use with the highest predicted probability is assigned to the grid. We then compare the predicted use with the observed use through two measures. The first one is the *hit rate by actual use*, which is the percentage of grids whose observed uses are correctly predicted. The second is the *hit rate by predicted use*, which is the percentage of grids whose predicted uses are confirmed by the observed use. Based on the two measures of prediction accuracy, the model performs quite well. The hit rates are 82 percent or better for all land use categories except urban land, which has a hit rate of 71 percent by actual use and of 70 percent by predicted use. Overall, the results suggest that the spatial panel model has strong in-sample predictive power.

The estimated coefficients for the land use model are presented in Appendix B, Table B.3. Most of the coefficients are statistically significant at the 1 percent level. Because the coefficients are difficult to interpret, we calculated the marginal effects at the weighted sample means using equation (7); the weighted means are calculated by weighting all values of variables using the initial proportions of land use in 1988. Because of the space limitation, we report only the marginal effects, by initial use, of road density and county GDP in Tables 2.2 and 2.3.

Table 2.2 reports the marginal effects of road density on the probability of land use change. Regardless of the initial use, higher road density increases the probability of being converted to farmland and urban use and reduces the probability of being converted to unused land. In contrast, the mathematical sign and statistical significance of the marginal probability of being converted to forests and grassland vary depending on the initial use. With increasing road density, the probability of farmland being converted to forests and grassland decreases, while the probability of unused land being converted to forests and grassland increases.

Table 2.2—Marginal effects of road density on the probability of land use change

Initial land use	Final land use					
	Farm	Forest	Grass	Water	Urban	Unused
Farm	0.8804***	-0.3749***	-0.4276***	-0.1258**	0.1277***	-0.0797**
	(0.1539)	(0.0667)	(0.0945)	(0.0564)	(0.0314)	(0.0322)
Forest	0.4402***	-0.2371**	-0.1628**	-0.0105	0.0152***	-0.0450**
	(0.0750)	(0.0956)	(0.0736)	(0.0092)	(0.0041)	(0.0206)
Grass	0.5224***	0.1664**	0.1132	-0.0105	0.0257***	-0.8171***
	(0.1220)	(0.0838)	(0.1211)	(0.0197)	(0.0065)	(0.2370)
Water	0.9213***	0.1103	0.1141	-0.7054	0.1253***	-0.5656**
	(0.3289)	(0.0953)	(0.2364)	(0.8171)	(0.0448)	(0.2575)
Urban	-0.0396	-0.1926***	-0.1986***	-0.1859**	0.6351***	-0.0186*
	(0.1245)	(0.0351)	(0.0442)	(0.0765)	(0.1662)	(0.0112)
Unused	0.2573***	0.1152***	0.9854***	0.0645**	0.0217	-1.4441***
	(0.0752)	(0.0372)	(0.2725)	(0.0307)	(0.0173)	(0.4126)

Source: Authors' estimation.
Note: We enlarge the magnitude of marginal effects by 100 times; *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.3 shows the marginal effects of county GDP on the probability of land use change. Regardless of the initial use, higher GDP increases the probability of being converted to urban use and reduces the probability of being converted to unused land. With economic growth, benefits from urban use increase relative to benefits from other uses, and local governments are more likely to approve urban development. Local government officials are also more likely to engage in political games to increase their promotion opportunities, which often involve public investments in *image projects* to show off their political achievements. Those image projects often require the conversion of large amounts of nonurban area to governmental, commercial, and industrial uses. The mathematical sign and statistical significance of the marginal probability of being converted to farmland, forests, and grassland vary with the initial use. Other things being equal, areas with higher GDP are more likely to convert grass and unused lands to crop production, which offsets farmland losses caused by urban development.

Table 2.3—Marginal effects of county GDP on the probability of land use change

Initial land use	Final land use					
	Farm	Forest	Grass	Water	Urban	Unused
Farm	0.0916***	0.0108	-0.1378**	0.0065***	0.0460***	-0.0172***
	(0.0268)	(0.0110)	(0.0188)	(0.0025)	(0.0031)	(0.0063)
Forest	0.0095	0.1436***	-0.1448***	0.0011**	0.0022***	-0.0116**
	(0.0119)	(0.0228)	(0.0187)	(0.0005)	(0.0005)	(0.0048)
Grass	0.1406***	0.1544***	-0.1591***	0.0114***	0.0080***	-0.1553***
	(0.0219)	(0.0205)	(0.0446)	(0.0020)	(0.0016)	(0.0537)
Water	-0.0007	0.0008	-0.1594***	0.3312***	0.0101***	-0.1820***
	(0.0151)	(0.0054)	(0.0225)	(0.0667)	(0.0025)	(0.0495)
Urban	-0.1658***	-0.0071	-0.0643***	0.0026	0.2387***	-0.0041*
	(0.0173)	(0.0048)	(0.0081)	(0.0032)	(0.0142)	(0.0022)
Unused	0.0548***	0.0313***	0.1762***	0.0239***	0.0050	-0.2912***
	(0.0149)	(0.0088)	(0.0637)	(0.0062)	(0.0040)	(0.0921)

Source: Authors' estimation.
Note: We enlarge the magnitude of marginal effects by 100 times; *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

3. THE CAUSAL EVALUATION MODEL OF SOC

In this section, we develop a statistical model to evaluate the effect of land use change on soil organic carbon (SOC) density. The propensity score–matching method is employed to eliminate the potential bias from endogenous treatment effects.

Conceptual Model

The dynamics of SOC flow are complex, with SOC storage being 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). Soil temperature, moisture, and texture jointly control the decomposition rates of SOC in various carbon pools (Parton et al. 1993); and their interactions display a complex, nonlinear pattern. For example, the effects of soil temperature and soil moisture on the decomposition rates exhibit an inverted-U shape with a heavy left tail. The decomposition rates of SOC in the active pool tend to increase with sand content, and the decomposition rates in the slow carbon pool tend to decrease with clay content. SOC density is negatively correlated with soil bulk density (Wang et al. 2004; Wu, Guo, and Peng 2003; Yang et al. 2007).

It is practically infeasible to apply detailed site-specific process models, such as Century (Parton et al. 1993), for a nationwide analysis because the collection of field-level soil and vegetation data is prohibitively expensive. Alternatively, one may explore the causal relationship of land use and SOC density using the treatment effect analysis. Assume that in a *natural* experiment, land use represents the treatment, denoted as a dummy variable D; a log-transformed SOC density is the outcome, denoted as C. A cause is viewed as a land use treatment that brings about a change in the SOC density outcome relative to the reference land use. Given any particular comparison unit n, the causal relationship of land use treatment and SOC density outcome can be expressed as

$$C_n = \alpha + D_n \tau + \mathbf{S}_n \boldsymbol{\gamma} + \xi_n , \tag{8}$$

where $\mathbf{S}_n$ are observable (pretreatment) covariates such as elevation, soil information, and weather conditions; α , τ, and $\boldsymbol{\gamma}$ are unknown coefficients on intercept, land use treatment, and covariates; and ξ_n represents random error. τ is usually referred to as treatment effect. That is, a conversion from the reference land use ($D_n = 0$) to an alternative use ($D_n = 1$) would cause τ unit changes in SOC density. The primary treatment effect of interest is the expected treatment effect for the treated population ($\tau|_{D=1}$).

A problem is that the comparison group is nonexperimental (nonrandomized). If pretreatment differences existed between a treatment group ($D = 1$) and a nonexperimental comparison group ($D = 0$), the estimate of a causal effect for the treated group ($\hat{\tau}|_{D=1}$) could be biased because of self-selection of the treated population (Dehejia and Wahba 2002). To correct the potential bias, matching methods have been developed in the econometric and statistical literature. The strategy is to pair the treated and comparison units that are similar in terms of their observable characteristics so that the outcomes with and without treatment are independent of the receipt of treatment after controlling certain pretreatment covariates (Rosenbaum and Rubin 1983). This method is straightforward in an application with a small number of pretreatment characteristics.

However, with a large number of pretreatment characteristics, it is difficult to match treated and comparison units in every dimension. One method to overcome this problem is the propensity score–matching method (Rosenbaum and Rubin 1983, 1985a, 1985b). This present study implements the propensity score–matching method to examine the causal effects of land use change on SOC density. Specifically, we adopt a strategy of single-nearest-neighbor matching with a replacement suggested by

Dehejia and Wahba (2002).[6] This strategy helps to reduce bias because it ensures a minimum distance of estimated propensity score from each treated unit to the matched comparison unit.

Data

Data used to estimate the SOC model also cover the whole of mainland China. Data on soil properties, including SOC density, were collected around 1985 as part of a special nationwide research and documentation project (the Second National Soil Survey of China) organized by the State Council and carried out by a consortium of universities, research institutes, and soils extension centers. CAS interpolated the information into surface data using the Kriging algorithm to get more disaggregated information for each pixel. To match the period when the soil profile information was collected, we use the 1988 land use data for the causal analysis. The causal evaluation model addresses the treatment effects of only four major uses—farmland, forests, grassland, and unused land—on SOC density because the effects of water and urban uses are negligible relative to the other major uses.[7]

After the adjustment for missing data, the cross-sectional dataset that is used for the causal analysis contains 91,531 observations. Table 3.1 provides the sample characteristics of each treatment. We conduct Tukey's HSD (honestly significant difference) test to compare the means of every treatment to the means of every other treatment simultaneously (Tukey 1953). The test results suggest that all pairwise comparisons are statistically different from zero at the 5 percent level. In addition, there are large pretreatment differences. For example, annual precipitation is approximately six times greater in forest areas than in unused land; in contrast, the soil pH and sand content are respectively 35 percent and 40 percent lower in forestland than in unused land. These data indicate potential self-selection in land use choices.

Table 3.1—Sample characteristics of the four major land uses in China

Variable	Farmland	Forests	Grassland	Unused land
SOC density (kgC m^{-2})	4.33 (3.88)	5.56 (4.29)	7.04 (7.10)	7.63 (5.72)
Annual precipitation (mm)	825 (419)	1038 (477)	379 (316)	147 (164)
Mean annual temperature (°C)	11.49 (5.56)	10.29 (7.78)	1.13 (6.58)	3.58 (6.75)
Elevation (m)	474 (616)	1081 (1059)	2927 (1786)	2257 (1662)
Soil PH value	5.62 (1.56)	4.75 (1.26)	6.62 (1.62)	7.26 (1.57)
Soil bulk density (g cm^{-3})	1.37 (0.13)	1.32 (0.14)	1.33 (0.14)	1.35 (0.17)
Soil loam content (%)	29.8 (7.2)	28.9 (6.6)	22.2 (8.9)	17.7 (10.0)
Soil sand content (%)	44.9 (11.6)	43.6 (10.9)	61.3 (15.1)	72.3 (14.9)
Sample size	17891	23304	30383	19953

Source: Authors' estimation.

Results

Using the single-nearest-neighbor propensity score–matching approach discussed above, we select 12 permutation groups from four major land use samples for pairwise analysis of treatment effects. The order of the treated group and the matched comparison group matters when the expected treatment effects for the treated population are asymmetric (that is, the effect of land use conversion from *j* to *l* on SOC density differs from the effect of land use change from *l* to *j*). Considering large pretreatment variations in land uses, we take into account the sequence of treatment to avoid potential bias from the symmetric assumption.

[6] Each treatment unit can be matched to the nearest comparison unit, even if a comparison unit is matched more than once.

[7] In addition, the number of conversion grids related to water and urban land is small, which may bias the estimates if the comparison unit does not match the treatment unit well.

Table 3.2 reports the results for all pairwise land use groups. The first two columns represent the treatment and the matched comparison subsamples, respectively. All of the units in the comparison group are selected within a predefined propensity-score radius (0.0001) so that the treated and compared units are similar enough to each other (columns 3 and 4). In all comparison samples, the standard errors of the estimated mean propensity score are larger than those in the corresponding treated samples. This may be because the sample size is smaller in comparison groups than in the treated.[8] Columns 5 and 6 show the size of treated and compared groups. Relatively few unused land grids (comparison units) match forest and farmland grids (treatment units), and vice versa. On the contrary, grids in grass and unused land are relatively more comparable. This result highlights the importance of sequential matching within pairs of land use groups.

Table 3.2—Estimated treatment effects for all pairwise land use groups

Treatment sample	Matched comparison sample†	Mean propensity score††		No. of observations		Treatment effect†††	
		Treatment	Comparison	Treatment	Comparison	Weighted sample average	Weighted conditional average
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Farm	Forest	0.58	0.58	13246	6520	-12.891***	-4.770***
		(0.26)	(0.37)			(0.866)	(0.693)
	Grass	0.67	0.67	11723	4823	-9.180***	-2.921***
		(0.28)	(0.44)			(1.060)	(0.829)
	Unused	0.91	0.91	8443	1306	-10.140***	-1.379
		(0.21)	(0.54)			(1.240)	(1.094)
Forest	Farm	0.70	0.70	18766	6603	3.410***	0.440
		(0.22)	(0.38)			(0.681)	(0.570)
	Grass	0.75	0.75	18999	5853	-7.910***	-3.540***
		(0.24)	(0.44)			(0.735)	(0.608)
	Unused	0.95	0.95	13275	1251	-0.540	-2.129**
		(0.16)	(0.53)			(0.806)	(0.869)
Grass	Farm	0.76	0.76	16126	4861	-3.850***	-4.914***
		(0.26)	(0.48)			(1.120)	(0.824)
	Forest	0.75	0.75	19533	5780	-30.660***	-7.344***
		(0.29)	(0.53)			(0.996)	(0.780)
	Unused	0.72	0.72	25889	8168	-6.120***	-5.751***
		(0.20)	(0.35)			(0.897)	(0.637)
Unused	Farm	0.84	0.84	5787	1288	-7.600***	0.480
		(0.29)	(0.62)			(1.760)	(1.463)
	Forest	0.92	0.92	11108	1239	-36.280***	-0.679
		(0.23)	(0.69)			(1.360)	(1.017)
	Grass	0.56	0.56	15396	7954	7.080***	7.143***
		(0.28)	(0.39)			(1.050)	(0.725)

Source: Authors' estimation.
Notes: † All of the comparison units are selected within a predefined propensity score radius (radius = 0.0001).
†† The propensity score is estimated using a logit of treatment status on precipitation, temperature, elevation, soil pH value, soil bulk density, soil loam content, soil sand content, and their interactions.
††† The magnitude of treatment effect (for the treated) is enlarged by 100 times; ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

By definition, the treatment effect is the expected change in log-transformed SOC density when a land parcel is converted from comparison use (column 2) to treatment use (column 1). Columns 7 and 8 report the estimated treatment effects for the treated population from two models—the weighted sample average and the weighted conditional average. Specifically, the weighted conditional average is estimated given a quadratic functional form of precipitation, temperature, elevation, soil pH, bulk density, and loam

[8] The characteristics of all matched subsamples are available upon request.

and sand contents; we also include site altitude and longitude as covariates to capture unobserved spatial heterogeneity and to improve the precision of the estimates.

A comparison of the results from the two models suggests that estimated treatment effects have the same sign except for the conversion from farmland to unused land. Most estimates from the two models are also consistent in statistical significance except when there are few comparison units (for example, unused land versus farmland or forest). We believe that estimates from the weighted conditional average model are more reliable than the weighted sample average model because the former controls pretreatment covariates, such as some plausible confounding factors (Dehejia and Wahba 2002; Imbens 2004). Controlling pretreatment covariates helps to avoid over- or underestimating the treatment effects. The analysis below is based on the estimated conditional average treatment effects presented in column 8.

Table 3.3 reports the treatment effect estimates in a transition matrix, where the *jl*th entry represents the estimated percentage change in SOC density caused by converting from land use *j* to land use *l*. The results highlight the asymmetry between land use changes in terms of their effects on SOC density. For example, converting forests to crop production will reduce SOC density by an average of 4.8 percent. In contrast, afforestation of farmland has a statistically insignificant effect on SOC density, implying that the loss of SOC caused by deforestation is irreversible in the short run. Converting farmland and forests to grassland decreases SOC density. But surprisingly, converting grassland to farmland and forests also decreases SOC density. Specifically, grassland encroachment into forest will reduce SOC density by 7.3 percent, the largest reduction among all land use changes. These results suggest that some SOC will be lost when unused land is converted to grassland. This may be because most of the unused land is located in gentle hillsides, ancient till platforms, and glaciofluvial deposits, where the climate is humid and frigid and organisms decompose slowly (Wang et al. 2001). Conversions between farmland and unused land have a statistically insignificant effect on SOC.

Table 3.3—Estimated percentage change in SOC density

	To farm	To forest	To grass	To unused
From farm	-	0.440	-4.914***	0.480
From forest	-4.770***	-	-7.344***	-0.679
From grass	-2.921***	-3.540***	-	7.143***
From unused	-1.379	-2.129**	-5.751***	-

Source: Authors' estimation.
Note: ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

4. SIMULATED EFFECTS OF ROAD CONSTRUCTION

China has made a tremendous amount of public investment in road network development in the last 20 years, with a 6.7 percent annual increase in the total length of all roads during the period 1988–2009 (NBSC 2001–2010, 2005). The road network development is still accelerating. From 2005 to 2009, the total road length in China increased 18.9 percent per year compared with an annual increase of 6.6 percent from 2000 to 2005.

Simulations are conducted to assess the effect of road construction on SOC density. Using the 2005 observations, we estimate the expected land use probability P_{nj}^{b} ($\forall j$) in each grid and use it as the baseline. From the standpoint of the simulations, we interpret P_{nj}^{b} as the expected percentage of land parcels in each grid allocated to use j.[9] The baseline SOC content of each grid is estimated using $SOC_{nj}^{b} = d_{n0j} \exp\left(C_n\right)\left(1+\sum_l \tau_{jl} P_{nl}^{b}\right)$, where d_{n0j} is the share of land use j within each grid in 1988[10]; τ_{jl} is the treatment effect when land is converted from j to l; $\tau_{jl} = 0$ if $j = l$ or if j, l = water, urban. The baseline acreage and SOC content and density for four major uses (farmland, forests, grassland, and unused land) are reported in Table 4.1. As shown, the mean SOC density is highest in grass and unused lands and lowest in farmland.

Table4.1—Baseline scenario

	Farm	Forest	Grass	Unused
Acreage (million ha.)	161.2	196.6	159.7	137
SOC content (PgC)	6.9	10.3	13.2	11.3
SOC density (kgC m^{-2})	4.3	5.26	8.28	8.25

Source: Authors' estimation.

The elasticity of land use probability with respect to variable X_n for each grid equals

$$e_{nj} = \partial \ln P_{nj} / \partial \ln X_n = \left[\left(\mathbf{I}_N - \rho \mathbf{W}\right)^{-1}\right]_{nn} \sigma_n^{-1}\left(\boldsymbol{\beta}_j - \sum_l P_{nl} \boldsymbol{\beta}_l\right) X_n . \tag{9}$$

Using the estimated 2005 land use share P_{nj}^{b} and the 2005 road density X_n, we calculate the elasticity and then assess how an increase in road density affects the SOC density. For an increase in road density by ΔX_n, the change in total acreage of each land use is calculated by

$$\frac{\Delta Area_j}{Area_j^b} = \frac{\sum_n P_{nj}^b e_{nj} \frac{\Delta X_n}{X_n}}{\sum_n P_{nj}^b} . \tag{10}$$

[9] Without loss of generality, we assume that individual land parcels have equal size within each grid.

[10] The causal evaluation model suggests that change in SOC density depends on the distribution of conditional probability of land use conversion. However, the available data do not allow a determination of the conditional probability within each grid. What we can estimate is the distribution of marginal probability of land use for grid size metric. Lacking better information, we assume that the distribution of marginal probability of initial land use is independent of the distribution of marginal probability of final land use within each grid.

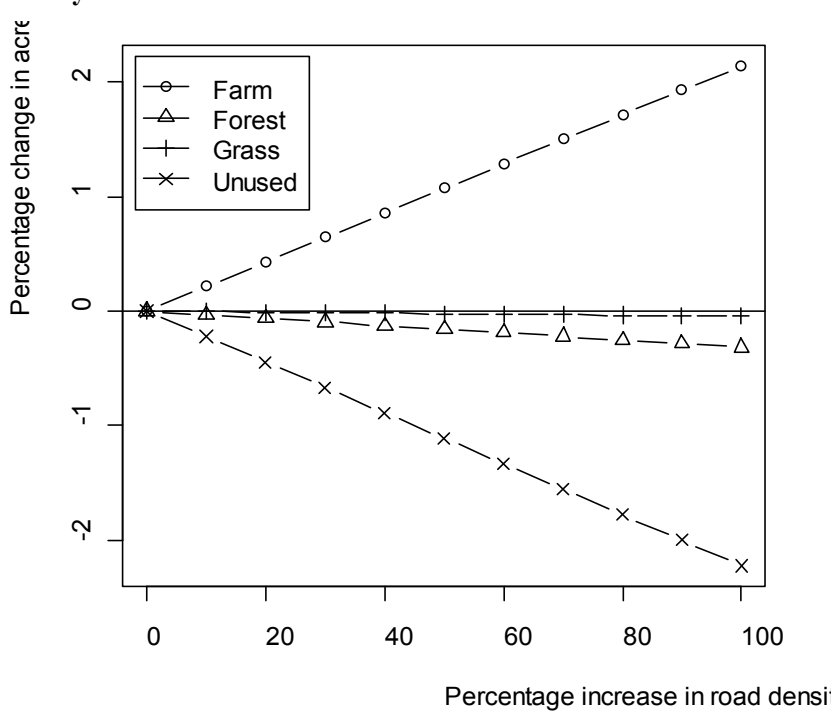
The corresponding change in total SOC content for each use can be derived as:

$$\frac{\Delta SOC_j}{SOC_j^b} = \frac{\sum_n d_{n0j} \exp(C_n) \sum_l \tau_{jl} \left(P_{nl}^b e_{nj} \frac{\Delta X_n}{X_n} \right)}{\sum_n d_{n0j} \exp(C_n) \left(1 + \sum_l \tau_{jl} P_{nl}^b \right)}. \tag{11}$$

Using equations (10) and (11), we estimate the changes in land acreage and SOC content as road density increases from 0 percent to 100 percent. Indeed, the total road length in China doubled from 2005 to 2010. In the baseline, the national average road density is 7.7 km/km^2. A 100 percent increase in road density increases the acreage of farmland by 3.46 million hectares and decreases the acreages of forests, grassland, and unused land by 0.62, 0.07, and 3.05 million hectares. These changes in land use lead to a net loss of approximately 11.8 teragram carbon (TgC) from farmland, forest, grass, and unused lands. Although the SOC content of farmland increases by 1.2 TgC, the SOC content of forest, grass, and unused lands decreases by 0.7, 7.9, and 4.3 TgC, respectively.

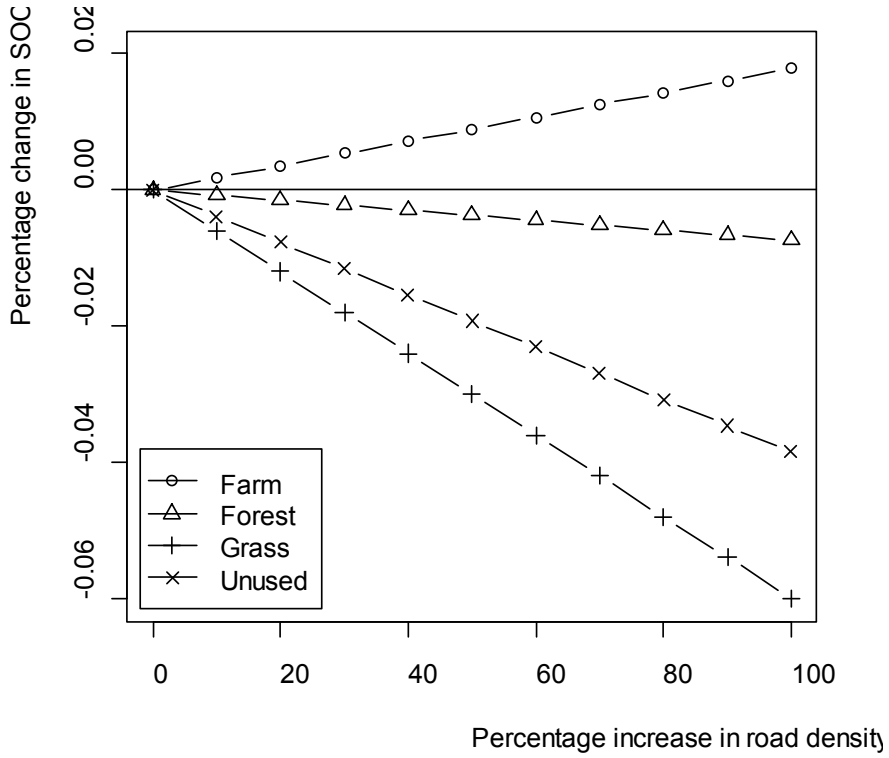
Figure4.1 and 4.2 show the percentage changes of acreage of farmland, forest, grass, and unused lands and of their SOC content as road density increases from 0 percent to 100 percent. The total acreage and SOC storage decrease for each use except farmland. Unused land loses most the acreage, while grassland loses the most SOC. According to our land use model, road construction not only induces conversions of grassland to farmland, but it also encourages conversions of unused land to grassland. Although the decrease in total acreage of grassland is relatively small, the resulting SOC loss is huge because converting grassland to any other land use will cause SOC loss. In contrast, the negative effects of road construction on forestland are more or less limited in terms of both acreage and SOC loss.

Figure4.1—Estimated percentage change in land acreage versus percentage increase in road density



Source: Authors' estimation.

Figure4.2—Estimated percentage change in SOC content versus percentage increase in road density



Source: Authors' estimation.

5. CONCLUSIONS

This paper develops an empirical framework to identify the major drivers of land use change in China and the resulting impact on soil carbon storage. The framework includes two main components. The first one is a land use model that takes into account the spatial and temporal dependence of land use choices explicitly. The second component is a soil organic carbon (SOC) model, which statistically evaluates the effect of land use change on SOC density. These models are estimated using a national geographic information system (GIS) database of land use, weather conditions, land quality, topographic features, and economic variables.

Results suggest that both economic and geophysical variables affected land use change in China. The level of local economic development, as measured by the county-level gross domestic product (GDP), was a major driver of converting grass and unused lands to crop production and urban development. Population pressure was not a major cause of deforestation, but expansion of road networks increased conversion of forestland to farmland. Road construction was also a primary cause of unused land loss. Other things being equal, farmland in areas with a higher yield potential, smaller slope, lower elevation, lower precipitation, and higher temperature was more likely to stay in agricultural use and less likely to be converted to forests and grassland. Conversely, forests and grassland in areas with those characteristics were more likely to become farmland and less likely to stay in those two uses.

The land use change has a significant effect on SOC density. Moreover, the impacts are asymmetric and vary by land use changes. SOC density always decreases, whether grassland is converted to farmland or farmland to grassland. The same is true for conversions between grassland and forestland. Converting forests to farmland causes a significant decrease in SOC density, but afforesting farmland only slightly raises the density, implying that the loss of SOC caused by deforestation is irreversible in the short run.

Combining the land use and SOC models, we assessed the effect of road network development on land use change and SOC in China. The total road length doubled in China from 2005 to 2010. This increased farmland by 3.46 million hectares and decreased forests, grassland, and unused land by 0.62, 0.07, and 3.05 million hectares, respectively. These changes in land use led to a net loss of SOC of approximately 11.8 teragram.

This big-picture study omits many details. Nevertheless, it provides useful information to policymakers responsible for the design of land use and conservation policies. Rapid economic growth has led to increased urbanization and substantial public investment in transportation infrastructure. As a result, the total road length has increased exponentially in the past 20 years in China. Building roads through, near, or to forests and grassland areas may improve the economic viability in those places, but it may also lead to deforestation and grassland degradation. From an environmental perspective, protecting forests and grassland is of substantial significance to China. Therefore, reducing public investment in transportation infrastructure in some ecologically sensitive areas may be an effective way to protect forests and grassland ecosystems.

APPENDIX A: PROCEDURE OF ESTIMATING THE SPATIAL PANEL MULTINOMIAL LOGIT MODEL

We experiment with three models by relaxing the assumption of spatiotemporal independent identical distribution (i.i.d.) of unobserved errors in a sequential fashion.[11] In the first model, we assume the unobserved errors are i.i.d. in the time dimension after controlling for spatial heterogeneity. We use seven geophysical variables—land quality, terrain slope, elevation, annual precipitation, mean annual temperature, standard deviations of annual precipitation, and standard deviations of mean annual temperature—to capture spatial heterogeneity explicitly. Terrain slope and elevation are generated from China's digital elevation model, which accounts for the information from neighboring parcels when estimating or retrieving values for a particular location during the interpolation process. Therefore, these variables in part capture spatial error dependence. We refer to this model as the cross-sectional multinomial logit model. We use the maximum likelihood method to estimate the log-likelihood function $LL = \sum_t \sum_n \sum_j d_{ntj} \ln P_{ntj}$.

In the second model, we relax the i.i.d. assumption in the time domain. Suppressing the land use subscript j, the temporal variance–covariance matrix of the unobserved random error between periods t and s takes the general form $E\left(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_s'\right) = \omega_{ts} \mathbf{I}_N, \forall\ t, s$, where $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\varepsilon}_s$ are N-dimensional vectors, ω_{ts} is a temporal covariance between t and s, and $\mathbf{I}_N$ is an N-dimensional identity matrix. We refer to this model as the SUR (seemingly unrelated regression) multinomial logit model. A major challenge to estimate using this model is the evaluation of an NT-dimensional integration ($T = 3$) in the likelihood function of the observed land use choices. To overcome this challenge, we assume $\omega_{ts} = 0$ if $t \neq s$. This assumption may lead to inefficient estimates. However, inefficiency is a much less important concern because we have a large number of observations. With this assumption, the joint probability density function is reduced to the product of marginal distributions for all individual observations in the time–space domain. Scaling equation (1) by $\omega_{tt}^{1/2}$ we estimate the coefficients $\boldsymbol{\beta}_j\ \forall\ j$ and variances $\omega_{tt}\ \ \forall\ t$ using the maximum likelihood method (BHHH-2 (Berndt, Hall, Hall, and Hausman) procedure; see Train 2003, pp. 199–200).

The third model, the spatial panel multinomial logit model, is defined by equations (5) and (6). It captures spatial lag dependence explicitly. When N is large, it is infeasible to estimate the spatial panel model using a traditional method based on log-likelihood function. An alternative approach is to apply the linearized generalized method of moments (GMM) by linearizing the generalized residuals around a convenient starting point, that is, $\rho_t = 0\ \forall\ t$ (Li, Wu, and Deng 2011; Klier and McMillen 2008). With the linearized model, the procedures are reduced to a standard logit (meaning nonspatial) followed by two-step least squares.

Specifically, let parameter vector $\boldsymbol{\theta} = (\boldsymbol{\beta}, \boldsymbol{\rho})$ and the gradient matrix $\mathbf{G} = \partial\mathbf{P}/\partial\boldsymbol{\theta}$. The gradient term for $\boldsymbol{\beta}$ and for $\boldsymbol{\rho}$ can be respectively expanded as

$$\frac{\partial P_{ntj}}{\partial \boldsymbol{\beta}} = P_{ntj}\left(\mathbf{1}\left(j = l\right) - P_{ntl|k}\right)\mathbf{X}_{nt}^{**}, \tag{A.1}$$

where $\mathbf{1}(j = l)$ is an indicator function which equals 1 when $j = l$ and zero otherwise, and

[11] The sequential fashion means that the second model is built on the first model, and the third model is built on the second model.

$$\frac{\partial P_{ntj}}{\partial \rho_t} = P_{ntj}\left[\left(\left(\mathbf{H}_t\right)_n \boldsymbol{\beta}_j - \frac{\mathbf{X}_{nt}^{**}\boldsymbol{\beta}_j}{\sigma_{nt}^2}\left(\boldsymbol{\Lambda}_t\right)_{nn}\right) - \sum_l P_{ntl}\left(\left(\mathbf{H}_t\right)_n \boldsymbol{\beta}_l - \frac{\mathbf{X}_{nt}^{**}\boldsymbol{\beta}_l}{\sigma_{nt}^2}\left(\boldsymbol{\Lambda}_t\right)_{nn}\right)\right], \tag{A.2}$$

where $\mathbf{H}_t = \left(\mathbf{I}_N - \rho_t \mathbf{W}\right)^{-1}\mathbf{W}\mathbf{X}_t^{**}$ and $\boldsymbol{\Lambda}_t = \left(\mathbf{I}_N - \rho_t \mathbf{W}\right)^{-1}\mathbf{W}\left(\mathbf{I}_N - \rho_t \mathbf{W}\right)^{-1}\left(\mathbf{I}_N - \rho_t \mathbf{W}'\right)^{-1}$. Note that $\boldsymbol{\Lambda}_t$ reduces to $\mathbf{W}$ if and the diagonal element $(\boldsymbol{\Lambda}_t)_{nn} = 0$ for all observations since $\mathbf{W}_{nn} = 0$. Therefore, when $\rho_t = 0 \ \forall \ t$, the gradient terms for $\boldsymbol{\beta}$ and for $\boldsymbol{\rho}$ reduce to

$$\frac{\partial P_{ntj}}{\partial \boldsymbol{\beta}} = P_{ntj}\left(\mathbf{1}\left(j = l\right) - P_{ntl}\right)\frac{\mathbf{X}_{nt}}{\sqrt{\omega_{tt}}}, \tag{A.3}$$

and

$$\frac{\partial P_{ntj}}{\partial \rho_t} = P_{ntj}\left[\frac{\left(\mathbf{W}\mathbf{X}_t\right)_n}{\sqrt{\omega_{tt}}}\boldsymbol{\beta}_j - \sum_l P_{ntl}\frac{\left(\mathbf{W}\mathbf{X}_t\right)_n}{\sqrt{\omega_{tt}}}\boldsymbol{\beta}_l\right], \tag{A.4}$$

In a multinomial logit model, the generalized residuals are simply $u_{ntj} = d_{ntj} - P_{ntj}$. Linearizing the generalized residuals equation around the initial estimates $\boldsymbol{\theta}^0 = (\boldsymbol{\beta}^0, \boldsymbol{\rho}^0)$, we have $u_{ntj} \approx u_{ntj}^0 - \mathbf{G}\left(\boldsymbol{\theta} - \boldsymbol{\theta}^0\right)$, which is equivalent to

$$u_{ntj}^0 + \mathbf{G}\boldsymbol{\theta}^0 \approx \mathbf{G}\boldsymbol{\theta} + u_{ntj}, \tag{A.5}$$

In this case, $\rho_t = 0 \ \forall \ t$ is a convenient starting point: $\boldsymbol{\beta}$ is estimated consistently by the SUR multinomial logit model and no matrixes need be inverted because $\left(\mathbf{I}_N - \rho_t \mathbf{W}\right)^{-1} = \mathbf{I}_N \ \forall \ t$. Equation (A.5) is the fundamental equation that will be estimated using the linearized GMM approach. Estimation includes the following steps:

1. Given the estimated parameters $\hat{\boldsymbol{\beta}}^0$ from the SUR multinomial logit model, the initial estimates for θ0 are $\boldsymbol{\theta}^0 = \left(\hat{\boldsymbol{\beta}}^0, \mathbf{0}\right)'$.
2. Based on the initial estimates, calculate the generalized residuals $u_{ntj}^0 = d_{ntj} - \hat{P}_{njt}$ and the gradient term G (see equations A.3 and A.4). Then we know the left side value of equation (A.5).
3. Regress G on instruments $\begin{pmatrix} \mathbf{X}_1 & \mathbf{W}\mathbf{X}_1 & \mathbf{W}^2\mathbf{X}_1 & \mathbf{W}^3\mathbf{X}_1 \\ \mathbf{X}_2 & \mathbf{W}\mathbf{X}_2 & \mathbf{W}^2\mathbf{X}_2 & \mathbf{W}^3\mathbf{X}_2 \\ \mathbf{X}_3 & \mathbf{W}\mathbf{X}_3 & \mathbf{W}^2\mathbf{X}_3 & \mathbf{W}^3\mathbf{X}_2 \end{pmatrix}$. Calculate the predicted value for G, which is expressed as $\hat{\mathbf{G}}$.
4. Regress $u_{ntj}^0 + \mathbf{G}\boldsymbol{\theta}^0$ on $\hat{\mathbf{G}}$. The coefficient estimates are estimated values of θ, expressed as $\hat{\boldsymbol{\theta}} = \left(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\rho}}\right)$, which are estimates for the spatial panel multinomial model.

APPENDIX B: SUPPLEMENTARY TABLES

Data and Estimation Results of Land Use Model

Table B.1—Summary statistics of explanatory variables in land use model

Variable	Measurement Unit	N	Mean	Standard Deviation	Minimum	Maximum
10-km-gird level [a]						
Land quality	1000 kg/ha.	68918	1.728	2.807	0.000	14.168
Terrain slope	degree	68918	3.091	4.154	0.000	66.250
Elevation	km	68918	1.333	1.342	-0.153	6.444
Precipitation, 1991-1995	1000 mm	68918	0.540	0.442	0.007	1.877
Precipitation, 1996-2000	1000 mm	68918	0.547	0.461	0.006	1.824
Precipitation, 2001-2005	1000 mm	68918	0.681	0.527	0.002	2.865
Precipitation, 2005	1000 mm	68918	0.692	0.532	0.000	3.025
Std. of precipitation, 1991-1995	1000 mm	68918	0.091	0.082	0.002	0.402
Std. of precipitation, 1996-2000	1000 mm	68918	0.092	0.070	0.002	0.368
Std. of precipitation, 2001-2005	1000 mm	68918	0.092	0.080	0.004	0.788
Temperature, 1991-1995	degree Celsius	68918	8.027	7.470	-16.440	24.820
Temperature, 1996-2000	degree Celsius	68918	8.412	7.498	-15.780	25.040
Temperature, 2001-2005	degree Celsius	68918	9.225	6.826	-4.696	26.295
Temperature, 2005	degree Celsius	68918	9.015	6.842	-4.656	26.013
Std. of temperature, 1991-1995	degree Celsius	68918	0.383	0.095	0.084	0.820
Std. of temperature, 1996-2000	degree Celsius	68918	0.561	0.120	0.239	1.144
Std. of temperature, 2001-2005	degree Celsius	68918	0.252	0.127	0.004	2.576
County level						
Road density, 1988 [b]	m/ha.	2034	0.751	1.656	0.000	41.877
Road density, 1995 [a]	m/ha.	2034	0.866	1.794	0.000	42.901
Road density, 2000 [b]	m/ha.	2034	1.043	2.136	0.000	47.960
Road density, 2005 [b]	m/ha.	2034	1.414	2.922	0.000	57.747
County GDP, 1989 [c]	billion CNY	2034	1.319	3.633	0.016	116.195
County GDP, 1996 [c]	billion CNY	2034	2.513	6.452	0.021	202.418
County GDP, 2000 [c]	billion CNY	2034	3.830	10.999	0.051	364.877
County GDP, 2005 [c]	billion CNY	2034	6.209	20.630	0.032	657.727
Population, 1989 [d]	million people	2034	0.481	0.460	0.007	10.228
Population, 1996 [d]	million people	2034	0.523	0.496	0.008	10.616
Population, 2000 [d]	million people	2034	0.543	0.516	0.008	10.817
Population, 2005 [d]	million people	2034	0.548	0.530	0.008	11.489
Agricultural investment, 1994 [e]	million CNY	2034	0.075	0.387	0.000	11.783
Agricultural investment, 1995-1999 [e]	million CNY	2034	0.076	0.417	0.000	13.354
Agricultural investment, 2000 [e]	million CNY	2034	0.095	0.527	0.000	17.057
Agricultural investment, 2005 [b]	million CNY	2034	0.156	0.920	0.000	25.563

Source: [a]. Chinese Academy of Sciences' remote sensing database; [b]. Authors' estimation; [c]. NBSC (2006); [d]. Ministry of Public Security of China (1996, 2001, 2006); [e]. Chinese provincial annual statistical yearbooks for each province for 1995 and 2000.

Table B.2—Prediction accuracy and predictive power assessment by land use category

Type	Land use category						Total
	Farm	Forest	Grass	Water	Urban	Unused	
Hit rate by actual use	0.931	0.947	0.901	0.823	0.711	0.939	0.926
Hit rate by predicted use	0.916	0.952	0.899	0.881	0.702	0.948	0.926
Number of observed grids	47,566	61,270	51,812	3,523	1,663	40,920	206,754
Number of predicted grids	48,351	60,942	51,927	3,291	1,685	40,558	206,754
Weighted Mean of probabilities†	0.686	0.777	0.710	0.565	0.322	0.873	-
Weighted Std Dev of probabilities†	0.126	0.130	0.137	0.061	0.045	0.095	-
Maximum of probabilities†	0.962	0.981	0.973	0.998	1.000	0.985	-
Minimum of probabilities†	0	0	0	0	0	0	-
Pearson correlation matrix of predicted probabilities							
Farmland	1						-
Forest	-0.278***	1					-
Grassland	-0.307***	-0.339***	1				-
Water area	-0.036***	-0.116***	-0.095***	1			-
Urban land	0.267***	-0.165***	-0.160***	-0.001	1		-
Unused land	-0.361***	-0.396***	-0.242***	-0.065***	-0.143***	1	-

Source: Authors' calculation.
Note: † Total number of observations = 206,754; weighted by initial land use in 1988.
*** indicates statistical significance at the 1% level.
Std Dev = Standard deviation.

Table B.3—Coefficient estimates for the spatial panel multinomial logit land use model

Independent variable	To Farmland		To Forests		To Grassland		To Water area		To Urban land	
	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Transition specific constants										
Initial farmland	2.5057***	(0.2601)	-0.9624***	(0.2628)	-0.8055***	(0.2542)	-3.7158***	(0.3115)	-0.7922***	(0.2887)
Initial forests	0.2280	(0.2382)	3.4637***	(0.2247)	0.0173	(0.2282)	-5.1057***	(0.3614)	-2.8433***	(0.3898)
Initial grassland	-1.4858***	(0.1276)	-1.6558***	(0.1225)	1.5193***	(0.1067)	-5.9869***	(0.1959)	-3.7916***	(0.2694)
Initial water area	-2.8237***	(0.2337)	-4.1741***	(0.2578)	-3.1276***	(0.1912)	0.6772***	(0.2077)	-4.0751***	(0.3638)
Initial urban land	4.3062***	(1.2476)	1.5624	(1.2991)	1.2635	(1.2316)	0.6769	(1.3532)	8.9903***	(1.2518)
Initial unused land	-6.0431***	(0.1659)	-6.7024***	(0.1897)	-4.9595***	(0.1229)	-8.4808***	(0.1969)	-7.9315***	(0.6500)
Time-invariant variables										
Land quality	0.1638***	(0.0300)	0.1290***	(0.0301)	0.1091***	(0.0289)	0.1719***	(0.0317)	0.1616***	(0.0312)
Terrain slope	0.0235***	(0.0054)	0.0455***	(0.0047)	0.0327***	(0.0040)	-0.0087	(0.0087)	-0.0644**	(0.0283)
Elevation	0.1586***	(0.0363)	0.2364***	(0.0263)	0.3633***	(0.0231)	0.7405***	(0.0375)	-0.0179	(0.0658)
Time-varying variables										
Precipitation	-0.0009***	(0.0001)	0.1610***	(0.0072)	0.0083***	(0.0030)	0.3053***	(0.0930)	-0.2984***	(0.0719)
Temperature	0.0929***	(0.0074)	0.0794***	(0.0070)	0.0741***	(0.0065)	0.1168***	(0.0104)	0.0936***	(0.0092)
Std Err of precipitation	11.6942	(0.9119)	12.4633**	(0.8982)	11.7241**	(0.8669)	15.3041**	(1.0113)	14.6484**	(0.9631)
Std Err of temperature	-0.3784**	(0.1606)	-0.4585***	(0.1320)	0.0536	(0.1011)	0.7806***	(0.1805)	-0.4406**	(0.2244)
Road density	0.3036***	(0.0640)	0.2428***	(0.0596)	0.2187***	(0.0512)	0.1920***	(0.0730)	0.3238***	(0.0666)
County GDP	0.0645***	(0.0133)	0.0649***	(0.0132)	0.0394***	(0.0118)	0.0687***	(0.0134)	0.0745***	(0.0133)
Population	0.0100	(0.0107)	0.0060***	(0.0020)	0.0003	(0.0002)	0.0001	(0.0001)	-0.0038***	(0.0005)
Agricultural investment	-0.0026**	(0.0005)	-0.0005***	(0.0001)	0.0051***	(0.0016)	0.0088***	(0.0012)	-0.0205***	(0.0020)
Spatial parameter (p)					0.0295***	(0.0018)				
Number of observations					1033770†					

Source: Authors' estimation.
Note: Std Err = Standard Error. ** and *** indicate statistical significance at the 5% and 1% levels, respectively; † 1033770 = 206754 × (6 – 1).

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