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Empirical Analysis of Land-use Change and Soil Carbon Sequestration Cost in China

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This project examines the driving forces behind the land-use change and evaluates the effects of land-use transition on soil organic carbon density and sequestration cost in China. It contributes to the literature in three aspects. First, it applies a discrete choice method to model multiple land-use options with a unique set of high-quality data. Second, it conducts a comprehensive analysis of biophysical characteristics and changes in soil carbon storage caused by land-use change. Third, it examines the economic efficiency of alternative land use policies as instruments for carbon sequestration in China.

Key words: carbon sequestration, land-use, soil organic carbon density, China

Increased concern over global climate change has brought great attention to China's carbon dioxide emissions. From 1991 to 2004 China doubled its carbon dioxide emissions due to the increased energy consumption (Marland *et al.* 2007). In 2006, China surpassed the United States to become the largest emitter of carbon dioxide in the world, releasing 6.2 billion tons of carbon dioxide into the atmosphere each year. The emission affects China as well as countries. For example, due to the greenhouse effect, China has witnessed many negative environmental impacts, including changes in planting seasons for some crops, shrinkage of inland lakes and tundra, and increases in the

intensity of drought and flood.

Increasing energy demand, driven by fast economic development and unprecedented urbanization, makes it a limited strategy to rely on energy-based abatement alone. As a supplement, biological carbon sequestration has gained more attention due to its forward-looking, multi-benefits for sustainable economic development, environmental conservation, and food security. Biological sequestration involves managing land in ways that enhance the natural absorption of atmospheric carbon by vegetation and soil.

With the total land area of 932.7 million hectares, China, like the United States and Canada, has a large potential for soil carbon sequestration. China has witnessed a remarkable land-use conversion over the past two decades, which has changed the storage of soil carbon significantly. According to a recent study, China losses 1.95 percent of soil organic carbon in its cropland annually, and the largest losses take place in the northeastern regions, which include the most fertile soils in the country (Tang *et al.*, 2006). Therefore, understanding the relationship between land-use change and soil carbon sequestration becomes an urgent issue.

This paper evaluates the impacts of land-use change on China's soil organic carbon (hereafter SOC) density and estimates sequestration costs under four land policy scenarios. To achieve these objectives, we first develop an econometric model of discrete land-use choice among six alternatives: farmland, grassland, forestland, water area, urban area, and unused land. The expected utilities are modeled in terms of characteristics of

individuals and alternatives, which is a combination of multinomial and conditional logistic formulations. We then develop a biometric model to assess the regional pattern of SOC density in China. The biometric model includes four types of variables – climate, soil physical and chemical properties, land-use category, and regional dummy. This approach can easily be applied to a large region and thus overcomes the limitation of a detailed site-specific, field-level process model. Finally, by combining the econometric and biometric models, we are able to use a revealed-preference approach to estimate sequestration cost (Stavins 1999).

The data come from three sources. The Chinese Academy of Science (CAS) provided data on land use, soil property, and socioeconomic variables. CAS compiled the land use panel data (1988, 1995, and 2000) based on the US Landsat TM/ETM images with a spatial resolution of 30 by 30 meters. Geophysical cross-sectional variables come from a geographical information system (GIS) database at a 1 by 1 square kilometer level. Socioeconomic variables are available at the county-level (with a few exceptions) from various editions of statistical yearbooks of China. In the current version of the paper, we conduct a case study on Huang-Huai-Hai Plain, which includes 9 provinces/provincial-level metropolis and 421 counties.

The paper makes several contributions to the literature. First, it analyzes multiple land-use options in China with a discrete choice model. Previous literature on land use in China mainly focuses on aggregate changes at the county level or above. To the best of

our knowledge, no one has assessed land allocation among multiple uses with a discrete choice approach in the literature. This method allows us to model land use at a very disaggregated scale, which is necessary for analyzing the environmental impacts of land use changes. Second, it considers economic efficiency and involves some socioeconomic variables in the model. In contrast, previous studies of China's carbon sequestration typically develop biophysical and biochemical models. Third, it examines the economic efficiency of alternative land use policies such as urban development control and farmland protection as instruments for carbon sequestration in China. Most previous studies have been limited to the cost analysis of afforestation policies.

Economic efficiency is a major criterion for evaluating the feasibility of alternative carbon sequestration strategies. However, previous literature of carbon sequestration in China typically involves biophysical and biochemical modeling without taking socioeconomic factors into account. With the databases of China's National Forest Resource Inventory (1949-1998) and China's Second National Soil Survey (1979-1985), many Chinese scholars have sought to assess the spatial pattern and change of carbon storage in forest and soil in China over the last decade. The land areas covered in previous studies include forestland (Fang *et al.* 2001), cropland/farmland (Tang *et al.* 2006; Zhang *et al.* 2006), and all types of lands (Wang *et al.* 2003; Wang *et al.* 2004; Wu *et al.* 2003; Yang *et al.* 2007). Huang and Sun (2006) conduct a nice survey on the changes in topsoil carbon of China's croplands over the last two decades by selecting 132

representative articles from literature databases published since 1993. Internationally, Canadian and Chinese collaborators execute a four-year (2002-2006) project of carbon sequestration in China's forest ecosystems. The achievements of the project are published in a special issue of *Journal of Environmental Management* (2007). Three biochemical/biophysical models are widely applied to the estimation of carbon storage: **Den**itrification-**Dec**omposition (DNDC), **In**tegrated **T**errestrial **E**cosystem **C**-budget (InTEC), and the Bemmelen index (0.58) equation. A few cost-benefit analyses of afforestation include early work by Xu (1995) and recent efforts by Wang *et al.* (2007) and Zhou *et al.* (2007) in the Canadian-Chinese collaborative project.

Researchers have been analyzing the sequestration costs for almost two decades in the United States and European countries. Initial studies generally address the topics of measuring forest sequestration costs (Adams *et al.* 1993; Alig *et al.* 1997; Lubowski *et al.* 2006; Parks and Hardie 1995; Plantinga *et al.* 1999; Stavins 1999). Richards and Stokes (2004) conducted a comprehensive review of the literature on this subject and pointed out there were three approaches to modeling opportunity cost of foregone land use: bottom-up engineering studies, the sectoral optimization approach, and the revealed-preference econometric method. Subsequent efforts involve the assessments of economic potential for agricultural soil carbon sequestration such as conservation tillage adoption (Pautsch *et al.* 2001; Antle and Diagana 2003; Capalbo *et al.* 2004; Feng *et al.* 2006; Antle *et al.* 2007). After adjusting for the variation among the studies, it is reported

that in the United States, afforestation can sequester 250 to 500 million Mg C (Megagram of carbon) per year at a price range of 10 to 150 dollars per Mg C, whereas conservation tillage may generate 0.25 to 6.2 million Mg C in soil per year at a cost range of 50 to 270 dollars per Mg C. The cost estimates of conservation tillage are sensitive to the choice of baseline and the spatial heterogeneity of the area.

The organization of this paper is as follows. The next two sections describe the econometric and the biometric modeling structures. Then we report the estimation results and carry out an analysis. Section five estimates sequestration costs through a series of simulations and discusses policy implications. The final section contains some concluding comments.

An Econometric Model of Land-Use Change

Consider a risk-neutral landholder making land use choice decisions. The choice set contains six elements: farmland, grassland, forestland, water area, urban area, and unused land. Assuming that urban development is irreversible, that is, urban area will never be converted into other categories of land use, we are interested in land transitions from five starting land-use groups (farmland, grassland, forestland, water area, and unused land).

We perform an empirical analysis by combining McFadden (1973)'s conditional logistic formulation and traditional multinomial logistic method. The difference between them lies in model specification, where the multinomial approach specifies the expected utility in terms of the characteristics of individuals while McFadden's method specifies it

as a function of the attributes of alternatives. Land-use decision is a relatively complicated process thus the econometric model in this study involves both site-specific and choice-specific variables.

Specially, let subscript i be land plot index, n denote county, t represent time period, k and l be initial and final land use, respectively. Landowner's utility from converting land use k to land use l is specified as $U_{itl|k} = V_{itl|k} + \varepsilon_{itl|k}$, where $V_{itl|k}$ is the observable component and $\varepsilon_{itl|k}$ is the unobserved type I extreme value error.

$$(1) \qquad V_{itl|k} = V\left(\mathbf{z}_{it}, \mathbf{x}_{ntl}\right) = \mu_{lk} + \boldsymbol{\gamma}_{lk}\mathbf{z}_{it} + \mathbf{x}_{ntl}{}'\boldsymbol{\beta}_{lk}$$

where $\mathbf{z}_{it}$ is a vector of site-specific variables and $\mathbf{x}_{ntl}$ is a vector of alternative-specific regressors. $\mathbf{x}$ denotes socioeconomic variables and $\mathbf{z}$ is a vector of a site's natural attributes such as land quality and slope. We index $\mathbf{x}$ by n since the most disaggregated form of socioeconomic variables is often at the county level. We interpret μ_{lk} as land conversion coefficient, which partly captures the conversion costs from use k to alternative l.

The absolute magnitude of coefficient in logistic model has no economic interpretation. Hence we set the initial land-use k as the reference within each of five categories and normalize $\mu_{kk} = 0$ and $\boldsymbol{\gamma}_{lk} = \mathbf{0}$, which will avoids redundant parameters.

$$(2) \qquad \begin{aligned} P_{it+1l|k} &= \Pr\left(U_{itl|k} > U_{its|k}, \forall\ l \neq s\right) \\ &= \Pr\left(V_{itl|k} + \varepsilon_{itl|k} > V_{its|k} + \varepsilon_{its|k}, \forall\ l \neq s\right) \\ &= \Pr\left(\varepsilon_{its|k} - \varepsilon_{itl|k} < V_{itl|k} - V_{its|k}, \forall\ l \neq s\right) \\ &= \frac{e^{V_{itl|k}}}{\sum_s e^{V_{its|k}}} \end{aligned}$$

Therefore the probability of converting plot i from land-use k to land-use l at period $t+1$ is given by equation (2). The logarithm of odds of choosing l over k can be written as

$$(3) \qquad \log \frac{P_{it+1l|k}}{P_{it+1k|k}} = V_{itl|k} - V_{itk|k} = \mu_{lk} + \boldsymbol{\gamma}_{lk}\mathbf{z}_{it} + \mathbf{x}_{ntl}{}'\boldsymbol{\beta}_{lk} - \mathbf{x}_{ntk}{}'\boldsymbol{\beta}_{kk}$$

We estimate the parameters with maximum likelihood method using SAS version 9.2.

Biometric Soil Organic Carbon Model

The dynamics of SOC flow are a complex process. Previous studies suggest that the balance of carbon inputs from plant production and outputs controls SOC storage through a decomposition process (Jobbágy and Jackson 2000; Parton *et al.* 1993; Schlesinger 1977). The diagram of SOC flow in Century model (Parton *et al.* 1993) demonstrates the joint effects of soil temperature, moisture, and texture, which control the decomposition rates of SOC in various carbon pools. For example, soil temperature and soil moisture influence the decomposition rates at an inverted-U pattern with a heavy left-tail. By contrast, the effects of soil texture are much more complicated. Sandy soils tend to have higher decomposition rates of active carbon pool and more carbon loss due 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. Studies also show that SOC density is negatively correlated with soil bulk density (Wang *et al.* 2004; Wu *et al.* 2003; Yang *et al.* 2007).

In contrast to biophysical/biochemical carbon models applied in previous literature, we use a statistical method to describe the relationship of SOC density and four types of variables – climate, soil property, land use, and regional dummy – as shown in equation (4). Yang *et al.* (2007) find that such variables can explain 84 percent of the variations in SOC storage in China. Specially, we use a humidity index (defined as $humity\ index \equiv \frac{annual\ precipitation}{mean\ annual\ temperature+10}$) to replace precipitation and temperature as a proxy for the climate variable. This substitution avoids significant correlation between mean annual temperature and annual precipitation. Soil variables include soil PH value, soil bulk density, and content of soil loam, clay, and sand. To be consistent with the six categories of land-use choice in the econometric model, we partition land use into farmland, forestland, grassland, water area, urban area, and unused land. Finally, we use regional dummies to capture the unobserved characteristics that vary across regions of China.

$$
\begin{aligned}
SOC &= f\left(climate, soil\ property, region, landuse\right) \\
&= f\left(\underbrace{humidity\ index}_{climate}, \underbrace{soil\ PH, soil\ loam, soil\ sand, soil\ clay, bulk\ density}_{soil\ property}, \underbrace{landuse\ dummy}_{landuse}, \underbrace{regional\ dummy}_{region}\right)
\end{aligned} \tag{4}
$$

To guarantee the robustness of the model, we apply several statistic techniques to validate and test the specification of equation (4). There are three alternative criteria used for model selection: a) corrected Akaike's Information Criterion (AICc), b) Bayesian Information Criterion (BIC), and c) 5-fold Cross-Validation criterion (CV Press). AICc and BIC are penalized criteria, measuring the tradeoff between bias and variance (loosely,

complexity and precision) in model construction. Specifically, $AICc = 1 + \log\left(\frac{SSE}{n}\right) + \frac{2(p+1)}{n-p-2}$ and $BIC = n\log\left(\frac{SSE}{n}\right) + 2(p+2)q - 2q^2, q = \frac{n\hat{\sigma}^2}{SSE}$, where n is the number of observations, p is the number of parameters (including intercept), and *SSE* is sum of squares error. These two criteria indicate that a complex model (i.e., with more number of parameters) would be penalized. CV Press is a technique for assessing how the results of a statistical analysis will generalize to an independent dataset. For example, in a 5-fold cross validation, the sample is randomly partitioned into 5 subsamples. Of the 5 subsamples, a single subsample is retained as a validation dataset and the remaining 4 subsamples are used for estimation. **P**redicted **re**sidual **s**um of **s**quare (Press) is calculated by fitting the model estimated from four subsamples with the data from single validation subsample. The CV process is then repeated 5 times with each of the 5 subsamples are used for validation. By averaging the 5 Press's, we obtain a single estimation as a criterion for model selection. The advantage of this method is that all observations are used for both estimation and validation, and each observation is used for validation exactly once.

Under a procedure of random sampling without replacement, we start with partitioning the whole data into two subsets: one is named as the *training* dataset, composed of 75% of observations in the whole sample to select specification and to estimate model; the other is called the *test* dataset, which contains 25% of total observations and is used for validation. Then we assign a candidate biometric model that is specified as a quadratic polynomial of all quantitative regressors. A competing model is

composed of a subset of parameters in the candidate model. Given the *training* dataset, we use a stepwise procedure to rank all possible competing models according three criteria (AICc, BIC, and CV Press) in turn, with the one having the lowest values being the best. Next we use the *test* dataset to examine the robustness of model prediction by calculating the average sum of square error (ASE). The idea is similar to that behind cross validation process. However, CV press is a criterion for model selection, while here we use the *test* dataset for model validation. Finally we compare the ASE from the *test* dataset with the ASE the *training* dataset. If the former is less than or close to the latter, the model is robust and can generalize to an independent dataset.

The model selection results are very consistent under the three alternative criteria. All parameters are selected into the model. In addition, this model is robust for prediction. The ASE's of the *training* and *test* datasets are quite close, equaling 0.03938 and 0.03967 respectively (Three criteria selects a same model, so their ASE's are same).

Data

Case Study Area: Huang-Huai-Hai Plain

This study will cover the whole country. For the time being, we apply an analysis on a random sample from Huang-Huai-Hai Plain, which includes 9 provinces/provincial-level metropolis and 421 counties. We will keep working on the other regions and will finish the complete analysis soon. Huang-Huai-Hai Plain is located in low reaches of the Yellow, Huai, and Hai rivers within an area of 350×10^3 km^2, with 18.67 million ha of farmland

under cultivation. As a highly productive agricultural area, the Huang-Huai-Hai is often referred to as China's breadbasket (Shi, 2003). Soil texture in the region ranges from sandy loam to loamy clay, and soil pH generally ranges between 7.4 and 8.6. This is one of the most important agricultural regions in China (Yang and Janssen, 1997).

Figure 1. Location map of the soil profile in the Huang-Huai-Hai Plain

Data Description

The data come from three sources and are provided by the Chinese Academy of Science (CAS). Land-use data are from a unique database (Liu *et al.*, 2003; Deng *et al.*, 2006), which was developed based on the US Landsat TM/ETM images with a spatial resolution of 30 by 30 meters. The database includes time-series data for the late 1980s, the mid-1990s, and the late 1990s. This study uses 1988, 1995, and 2000 to denote the three time periods. There are 25 land use/cover classes. We group them into six land use categories – farmland, forestland, grassland, water area, urban area, and unused land. Table 1a reports the frequencies and the percentages of six land-use classes for three

periods. Farmland is a major component of the land base, accounting for 70.2% of the total land of the case study area in the initial year 1988. Urban is the second largest land-use category in the sample region. The land areas of forestland, grassland, water area, and unused land are relatively small. The share of farmland declined to 69.1% in 2000. The share of unused land decreases by 25%. In contrast, the share of urban area increased from 12.3% to 13.5% from 1988 to 2000.

Table 1a. Summary Statistics of Land-use categories

Land-use category	1988		1995		2000	
	Freq	Percent	Freq	Percent	Freq	Percent
Farmland	311170	0.702	303126	0.684	306618	0.691
Forestland	28805	0.065	36362	0.082	29084	0.066
Grassland	31356	0.071	27570	0.062	30834	0.070
Water area	13746	0.031	14157	0.032	14125	0.032
Urban area	54749	0.123	57810	0.130	60027	0.135
Unused land	3644	0.008	4437	0.010	2759	0.006
Observations	443470		443462		443447	

Data on geophysical variables come from a GIS database that includes all parameters of soil properties used in the biometric SOC model. The variables of soil attribute include SOC content, soil PH value, soil bulk density, soil loam, sand, and clay content. Information on the properties of soil is from the CAS data center. Originally collected by a special nationwide research and documentation project (the *Second Round of China's National Soil Survey*) organized by the State Council and run by a consortium of universities, research institutes and soils extension centers. By using a conventional Kriging algorithm (Kravchenko and Bullock 1999), we are able to interpolate the soil information into surface data to get more disaggregated information on the property of

the soil over space for each pixel.

The database also contains three variables used in the econometric land-use change model, i.e., land productivity, terrain slope, and highway density. Land productivity was included here was to measure the pixel-specific agricultural productivity (Deng *et al*, 2006), was introduced and used in our studies. The original values of the land productivity were estimated by the research team from Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences (CAS) by using the standalone software, Estimation System for the Agricultural Productivity (ESAP). The *terrain slope* variable, which measures the nature of the terrain of each county, are generated from China's digital elevation model data set that are part of the basic CAS data base. Based on a digital map of transportation networks in the mid-1990s, we measure *Highway density* as the total length of all highways in a county divided by the land area of the county. All of the geophysical variables are cross-sectional data at a 1 by 1 square kilometer level. The summary statistics of the geophysical variables is given in Table 1b.

Additionally, we use two climate variables, mean annual temperature and mean annual precipitation as proxies for soil temperature and soil moisture. The data for measuring *precipitation* (measured in millimeters per year) and *temperature* (measured in accumulated degrees centigrade per year) are from the CAS data center but were initially collected and organized by the Meteorological Observation Bureau of China. For use in

our study, we take the point data from the climate stations in our case study and interpolate them into surface data using an approach called the thin plate smoothing spline method (Hartkamp et al. 1999).

Table 1b. Summary Statistics of Geophysical Variables

Variable	Level	Mean	Std Dev
SOC Model			
SOC density (g/m2)	1 km2	2.23	0.62
Mean annual temperature (degree Celsius)	1 km2	12.79	1.52
Annual precipitation (mm)	1 km2	652.82	134.39
Soil PH	1 km2	6.56	0.74
Bulk density (g/cm3)	1 km2	137.53	3.50
Soil loam content (%)	1 km2	30.68	5.67
Soil sand content (%)	1 km2	59.15	9.84
Soil clay content (%)	1 km2	19.85	3.47
Percentage of inland	1 km2	29.72	n/a
Percentage of north coastal	1 km2	28.98	n/a
Percentage of middle coastal	1 km2	41.31	n/a
Land-use Model			
Land productivity (kg/km2)	1 km2	78.45	39.95
Terrain slope (degree)	1 km2	0.85	1.95
Highway density (km/km2)	county	0.06	0.06

From various versions of statistical yearbooks of China, we collected the socioeconomic data, mainly for years 1988, 1995, and 2000. Most of the socioeconomic data are at the county-level. Data in value terms are measured at the 2000 real yuan (in RMB ¥ 10^4). Table 1c reports the summary statistics of these time-series variables.

Table 1c. Summary Statistics of Time-series Variables

Variable	Level	1988-2000	
		Mean	Std Dev
Value-added of farming (¥10000 /year)	province	41964.20	23312.22
Value-added of forestry (¥10000/year)	province	2056.01	1238.67
Value-added of animal-husbandry (¥10000/year)	province	15060.02	7514.62

Agricultural investment (¥10000/km2/year)	county	0.20	1.37
Percentage of farmland converted to urban	county	0.13	0.05
Forest investment (¥10000year)	province	3158.08	1890.09
Afforetation project (1=yes, 0=no)	n/a	0.22	0.41
Net industry output (¥10000/km2/year)	county	926.69	6455.16
GDP per capita (¥10000 per person)	county	0.36	0.18
Average annual change in GDP (¥10000)	province	27449.35	23655.67
Std dev of annual change in GDP (¥10000)	county	169.60	57.90
Share of urban area	county	0.12	0.06
Nonrural population density (people per km2)	county	0.54	0.94

Ideally, we should use land rents to evaluate net returns on alternative land use. However, land in China is either state-owned (urban area) or collectively owned (rural area). Local governments, on behalf of the state, control all categories of land-use transitions. Therefore, the actual land rents do not exist in China. Furthermore, policy preference may guide a land-use pattern and dominate economic incentives even if there is an appropriate measure of land rents. Consequently, in addition to economic values, socioeconomic variables include some measures for policy factors.

The urban land rents merit a comment. In their influential article, Capozza and Helsley (1990) propose a structure of equilibrium land rent under uncertain circumstances. It provides a guideline for us to construct landholder's utility from urban use. Except for minor alterations, the theoretical urban land rent in this paper is identical to that in the stochastic monocentric urban model of Capozza and Helsley (1990). In particular, the average rent of urban area is given by $R = R_k + rC + \frac{r-\lambda g}{\lambda r} + \frac{\tau u^*}{2}$, where R_k denotes pre-conversion land rent, r is the discount rate, C is one-time conversion cost, τ represents the commuting cost of unit distance, and $u^*(t)$ is the distance from urban

boundary to the central business district. Specially, $\frac{r-\lambda g}{\lambda r}$ represents option value, which is a premium of irreversible urbanization arising from future uncertainty. λ is the defined as $\lambda \equiv \frac{\left(g^2+2\sigma^2 r\right)^{1/2}-g}{\sigma^2}$ and g and σ^2 are, respectively, the drift and the variance of Brownian motion rents. Option value will postpone a transition decision to urban area and an increase in uncertainty (σ^2) will result in a further delay since $\partial\left(\frac{r-\lambda g}{\lambda r}\right)\Big/\partial\left(\sigma^2\right)>0$.

We use net industry output per square kilometer to proxy for the basic part of urban land rents ($R_k + rC$). The option value ($\frac{r-\lambda g}{\lambda r}$) is approximated by a function of average annual change in GDP and the standard deviation of annual change in GDP. We use the share of urban area and highway density in a county to evaluate the value of accessibility ($\frac{\tau u^*}{2}$). As two supplements, we use gross domestic product (GDP) per capita and non-rural population density to capture the level of economic development and urban land capacity, respectively. Due to the large amount of missing observations of land-use area, we do not directly use the area share of urban land in a county to measure the share of urban area. By contrast, we use a county-level percentage of observations of urban land in the sample to proxy for the land area share. Specifically, we perform three separate simple linear regressions on observations in three periods, with a regressand of the land area share and a regressor of the percentage of observations. We hope the fit line to be a 45 degree line through the origin. This measurement is very robust with a range of R-square's is from 0.97 to 0.98. Intercept and slope estimates are close to zero and one,

respectively.

Based on the idea of augmented investment resulting in higher output, we use agricultural investment per square kilometer as proxies for rents of farmland. However, there are no appropriate measurements for land rents on forestland. So we employ a continuous variable of aggregate provincial forest investment and a dummy variable of natural forests protection project to examine the impact of afforestation policy on land-use change. We also use aggregate value-added of farm, forestry and animal-husbandry at a province-level as a gross measurement for return on farmland, forestland, and grassland.

The Basic Farmland Protection Regulation established in 1994 deserves some comments. The regulation aims at protecting cultivated land by prohibiting conversions of farmland to nonagricultural uses. It requires governments at the county-level or above to designate a basic farmland protection zone in every village or township. The same amount of farmland lost must be replaced by new farmland somewhere else if there was an inevitable land conversion within a protection zone. This requirement is also called "dynamic balance". To capture this policy's influence on transition from non-farmland to farmland, we define a variable of percentage of urbanized farmland conditional on being in initial farmland use (i.e., divide the observed number of urban land parcels which were initially farmland in a county by the total observed amount of farmland parcels of that county in the starting period). This variable enters forestland, grassland, water area, and

unused land model as a covariate. The idea behind constructing this variable is that, if "dynamic balance" has impacts on land transition from non-farmland to farmland, an increase in the percentage of urbanized farmland will raise the probability of non-farmland converted to farmland.

Estimation and Results

Parameters of separate models are estimated conditional on each of five starting land-use. We employ two versions of econometric model by constructing data in two ways. First, we drop variables in 1995 and conduct a cross-sectional analysis. Second, we estimate the model using panel data with two time intervals 1988-1995 and 1995-2000. The second model of panel data also involves fixed-time effects to capture the unobserved time-dependent errors. The estimation results of two models are quite close, even though most of the fixed-time effects are statistically significant. Minor differences lie in that the goodness-of-fit of cross-sectional model is slightly lower than that of panel data model when beginning with farmland, and a bit higher if starting with forestland, grassland, and water area. In terms of initial unused land, panel data model performs better than cross-sectional model, indicating that there might be some unobservable time-dependent factors influencing the transition probability of unused land.

We will interpret estimation results and estimate costs of carbon sequestration based on the cross-sectional model for two reasons: 1) it may avoid a server econometric problem of error correlation over time, 2) unused land only accounts for less than 1

percent of the total land base, which is not of our major concern. To save space, we only present the results of cross-sectional model (1988-2000).

Table 2 shows the frequency and probability of land transitions from 1988 to 2000. Urban expansion is a remarkable phenomenon and farmland, as the largest component of land base, is the main source of urbanization. There is 13.2 percent of farmland converted to urban area from 1988 to 2000, accounting for 93.7 percent of the total urbanized land parcels. In contrast, urban expansion from non-farmland is negligible. Meanwhile, forestland, grassland, water area, and unused land are converted to farmland in a percentage of range between 19.0 and 46.8. Land transitions between forest and grass, as well as land changes from unused land to water area, also account for a relatively large percent of their respective initial land-use area.

Table 2. Land Transitions from 1988 to 2000

Initial land-use		Final land-use					
		Farm 1988-2000	Forest 1988-2000	Grass 1988-2000	Water 1988-2000	Urban 1988-2000	Unused 1988-2000
Farm	Freq	200962	4123	7017	4365	33158	896
	Prob	0.802	0.017	0.028	0.017	0.132	0.004
Forest	Freq	4371	14331	3496	283	500	30
	Prob	0.190	0.623	0.152	0.012	0.022	0.001
Grass	Freq	6623	4234	13236	454	760	79
	Prob	0.261	0.167	0.521	0.018	0.030	0.003
Water	Freq	4771	245	392	3964	743	74
	Prob	0.468	0.024	0.039	0.389	0.073	0.007
Unused	Freq	996	55	118	628	233	818
	Prob	0.350	0.019	0.041	0.221	0.082	0.287

Table 3 reports the estimation results for five classes of initial land-use. It indicates an accessible McFadden's likelihood ratio indices (LRI) for the models starting with

farmland and with forestland, which fit variations in land transition by 63.71% and 50.26%, respectively. By contrast, McFadden's LRI's are relatively low for the remaining three models (initially used as grassland, water area, and unused land). Insufficient covariates are a suspectable reason for the low indices. Despite that, this model can explain well on probability of urban expansion and conversion to farmland, which are two main transitions of land-use in the sample region over 1988-2000.

Table 3. Coefficient Estimates for the Econometric Land-use Change Model

	Initial Land-use	Farmland	Forestland	Grassland	Water area	Unused land
	Parameter	Coefficient Estimates				
Farm	Intercept	n/a	-1.2448***	-1.1038***	-0.9064***	0.4961
	Land prod	n/a	0.0275***	0.0178***	0.0143***	0.0217***
	Terrain slope	n/a	-0.3597***	-0.2433***	0.4289***	-0.3727**
	Value-added	0.0000**	-0.0000***	0.0000***	-0.0000	0.0000***
	Value-added*Land prod	-0.0000***	-0.0000	-0.0000***	0.0000	-0.0000**
	Log(agri inv)	0.0076	-0.0225	-0.0049	-0.0615***	-0.2674***
	Log(agri inv)*Land prod	-0.0000	0.0006*	0.0004	0.0007**	0.0011
	% of farm to urban	n/a	1.8947**	2.8843***	2.712**	-45.5231***
	(% of farm to urban)^2	n/a	-6.7948***	-11.5495***	-10.0875**	176.3782***
Forest	Intercept	-2.8087***	n/a	-1.2914***	-3.2965***	-2.3713**
	Land prod	-0.0161***	n/a	-0.0085***	-0.0024	0.0040
	Terrain slope	0.8256***	n/a	0.3300***	1.1931***	1.6771***
	Value-added	-0.0000	-0.0004***	0.0001	-0.0000	0.0001
	Value-added*Land prod	0.0000	0.0000***	0.0000	0.0000	-0.0000
	Forest inv	-0.0002***	-0.00002	-0.0001***	-0.0000	-0.0008**
	Forest inv*terrain slope	-0.0000	-0.0000**	-0.0000***	-0.0000	0.0000
	Afforest proj(0-1 indicator)	-0.2014***	0.1900**	0.0481	0.3708*	1.7232***
	Afforest proj*terrain slope	-0.0357**	-0.0137	-0.1356***	-0.1996**	0.0246
Grass	Intercept	-2.4612***	-0.7396***	n/a	-2.3083***	-2.7742***
	Land prod	-0.0196***	-0.0044***	n/a	-0.0070**	-0.0038
	Terrain slope	0.7541***	-0.1240***	n/a	1.0923***	1.3685***
	Value-added	-0.0000***	-0.0001***	0.0000	-0.0000**	0.0000
	Value-added*Land prod	0.0000*	0.0000***	-0.0000	0.0000	0.0000
Water	Intercept	-2.6657***	-3.2129***	-2.0342***	n/a	0.0867
	Land prod	-0.0139***	0.0109***	-0.0024	n/a	-0.0057***

	Terrain slope	-0.1816***	-0.5535***	-0.6032***	n/a	-2.4208***
Urban	Intercept	-2.3884***	-3.7900***	-3.9661***	-2.8172***	-0.4540
	Land prod	-0.0036***	0.0211***	0.0008	0.0126***	-0.0105***
	Terrain slope	-0.1368***	-0.5510***	-0.4078***	0.3222***	0.4245*
	Log(value-added)	0.0906***	0.0114	0.0582	-0.0663	-0.7616***
	GDP per capita	-0.8707***	-0.9118	1.0585*	-1.3308**	3.4384**
	(GDP per capita)^2	0.3247***	1.0422*	-0.6771	1.0557**	-1.8127
	Ave change in GDP	0.0000***	-0.0000***	-0.0000	0.0000	-0.0000***
	Std dev of change in GDP	-0.0011***	-0.0018**	0.0003	0.0002	0.0042**
	Share of urban area	5.3337***	9.151***	11.3836***	5.4702***	11.1822***
	Highway density	-0.0860	0.7409	3.5149***	0.5017	1.7424
	Nonrural pop density	0.0188	0.5661	0.2871*	0.2731	2.9210***
	(Nonrural pop density)^2	-0.0028	-0.4701	-0.0171*	-0.0212*	-0.1819***
Unused	Intercept	-3.9288***	-5.5999***	-3.9534***	-3.4310***	n/a
	Land prod	-0.0178***	0.0136**	0.0013	-0.0096***	n/a
	Terrain slope	-0.3730***	-0.5393***	-0.5927***	-0.8097*	n/a
Number of observations		250611	23011	25386	10189	2848
McFadden's LRI		0.6371	0.5026	0.4021	0.3982	0.2845

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

In general, almost all of site-specific variables are statistically significant at 1% level or less. As anticipated, lands with higher productivity tend to be converted to farmland and urban area and lands with higher slope are more likely to be changed into forestland. The conversion coefficient estimates (intercept) are negative and statistically significant, which is in line with the expected economic interpretation.

Most of explanatory variables for urban expansion are significant and have the expected signs. For instance, an increase in net industry output will accelerate lands converted to urban. The negative and statistically significant sign of standard deviation of change in GDP provides an evidence for option value proposed by Capozza and Helsley (1990), i.e, increased uncertainty will delay an irreversible urbanization. The influence of share of urban area on urban expansion deserves more concerns, which is statistically

significant at 1% level for all of five initial alternatives. In this sense, a highly urbanized area tends to requisition more lands from the remaining five classes of non-urban land. In contrast to the share of urban area, highway density is not significant except for initial grassland. Non-rural population exhibit an inverted-U curve and statistically significant for initial unused land use, but marginal significant or insignificant for other cases. These results indicate that land conversion from different initial use to urban area is sensitive to different components of the theoretical urban land rents.

We report own-return elasticity of land-use choice in table 4 by selecting some representative variables. Elasticity is defined as a percentage change in the probability of choosing the final land-use conditional on being in the initial use, for a 1% change in the variable to the final use. We evaluate elasticity at the means of data. Generally, the signs of value-associated own-return elasticity are unstable, while the signs of policy-related elasticity are consistent. For example, the elasticity with respect to agricultural investment is positive given initial use in farmland and grassland. Forestland is insensitive to forest investment. Except for unused land, all other lands respond to the percentage of land parcels converted from farm to urban as anticipated.

Table 4. Own-return Elasticity of Land-use Choice

Initial land-use	Final land-use										
	Farm			Forest		Grass	Urban				
	log(AgrI)	A-value	Prob	forestI	A-value	A-value	log(Ind)	Std gdp	Urban	Highway	Pop
Farm	0.002	-0.006	n/a	-0.509	0.016	-0.032	0.485	-0.163	0.599	-0.005	0.009
Forest	-0.016	-0.335	0.020	-0.061	-0.174	-0.567	0.079	-0.265	0.759	0.028	0.307
Grass	0.020	0.144	0.051	-0.606	0.153	0.014	0.395	0.050	0.765	0.134	0.140
Water	-0.022	-0.061	0.011	-0.132	0.090	-0.252	-0.389	0.038	0.605	0.027	0.138
Unused	-0.399	0.599	-0.599	-2.409	0.178	0.435	-3.106	0.567	0.846	0.084	2.381

Soil Organic Carbon Model

The SOC density is sensitive to geophysical location. Therefore we split the plain into three regions (inland, north, and south) in the following analysis[1]. Table 5 reports coefficient estimates of the biometric SOC model. The results indicate good fit of the model. Specially, it can explain 89.78 percent of variation in SOC density. Within 99 parameters, only 7 ones are not statistically significant at a 5% level or above. We examine the signs of climate and soil variables with a linear model, which allows us purging the disturbance from the square and interaction terms in the quadratic specification. The signs of variables are generally as expected. For example, SOC density increases in humidity index and decreases in soil sand and soil clay content in most regions. An increase in soil PH value and soil bulk density also cause a reduction of SOC density. In summary, the estimated signs of climate and soil parameters are robustly in line with the scientific rationale proposed by pedological and ecological literature.

The coefficient estimates of land-use categories are of our interest. As shown in Table 2, the marginal effects of land-use change on SOC density exhibit great spatial heterogeneity. Farmland has a similar SOC density to urban area, where the density is a bit higher than that of farmland in the north region and slightly lower in the other two. Deforestation generally lowers SOC density in the sample region except for converting

[1] Inland region includes Shanxi and Henan provinces. North area contains Beijing city, Tianjian city, and Hebei and Liaoning provinces. South region is composed of Jiangsu, Anhui, and Shandong provines.

forestland to grassland in the inland area. In the north coastal region, land converted from forest to farm and grass suffers losses 0.084 and 0.089 gram C per square meter, respectively. In the inland region, land transition from forest to farm loses 0.237 gram C per square meter. By contrast, the distribution of SOC density in grassland varies greatly across regions. It is high in the inland region and is very low in the north area.

Table 5. Coefficient Estimates for the Biometric SOC Model

	Qquadratic Model			Linear Model		
	Inland	North	South	Inland	North	South
Variables	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Intercept	35.7000***	-45.7537***	6.5938***	4.0113***	2.1006***	0.8809***
Farmland	0.0323*	0.1407***	-0.0066	0.0492*	0.3430***	-0.0948***
Forestland	0.2696***	0.2245***	0.0459***	0.26835***	0.6870***	-0.0890***
Grassland	0.2756***	0.1351***	0.0287***	0.4124***	0.5789***	-0.0858***
Water area	0.0666***	0.1474***	-0.0023	0.0623**	0.3421***	-0.1152***
Urban area	0.0214	0.1616***	-0.0096*	0.0305	0.3735***	-0.0891***
Humidity index	-0.0801***	0.2537***	-0.3259***	0.0083***	0.0247***	-0.0049***
Soil PH value	0.6611***	-5.4712***	0.1466***	-0.0277***	0.1744***	-0.0638***
Soil loam	0.05496***	-0.3037***	-0.06115***	-0.0098***	0.0047***	0.0154***
Soil sand	0.3268***	-0.2276***	0.1385***	-0.0015***	0.0269***	-0.0075***
Soil clay	-1.5410***	-0.0660**	-0.4167***	-0.0618***	0.1254***	-0.0061***
Soil bulk density	-0.3661***	1.0770***	0.0090***	-0.0029***	-0.0405***	0.0126***
(Humidity index)^2	0.0026***	-0.0019***	0.0022***			
(Soil PH value)^2	0.0029***	0.0320***	-0.0043***			
(Soil loam)^2	-0.0029***	-0.0036***	0.0006***			
(Soil sand)^2	0.0007***	-0.0003***	-0.0003***			
(Soil clay)^2	-0.0003***	0.0014***	-0.0016***			
(Soil bulk density)^2	0.0008***	-0.0053***	0.0002***			
Humidity index*soil PH value	-0.0150***	0.0035***	-0.0085***			
Humidity index*soil loam	0.0009***	-0.0024***	-0.0002***			
Humidity index*soil sand	0.0035***	0.0065***	0.0014***			
Humidity index*soil clay	-0.0007***	-0.0044***	0.0080***			
Humidity index*soil bulk density	-0.0013***	-0.0030***	-0.0000			
Soil PH value*soil loam	0.0105***	0.0093***	-0.0027***			
Soil PH value*soil sand	-0.0034***	0.0081***	-0.0036***			
Soil PH value*soil clay	-0.0030***	-0.0036***	0.0053***			

Soil PH value*soil bulk density	-0.0023***	0.0324***	0.0021***			
Soil loam*soil sand	-0.0013***	-0.0016***	-0.0000			
Soil loam*soil clay	0.0010***	0.0005***	0.0011***			
Soil loam*soil bulk density	0.0004***	0.0044***	0.0003***			
Soil sand*soil clay	-0.0050***	-0.0015***	0.0016***			
Soil sand*soil bulk density	-0.0024***	0.0010***	-0.0012***			
Soil clay*soil bulk density	0.0130***	0.0022***	0.0004***			
Observations	71929	95151	163953	71929	95151	163953
Total number of observations		331033			331033	
R-Square		0.898			0.789	

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

Simulation

We estimate carbon sequestration costs with several policy simulations at a 1 by 1 square kilometer level. To be specific, we predict land transition probability with the results of econometric model. The total land area can be normalized to one because each of land-use observations is gathered at the same level (1 by 1 square kilometer). After weighted by the percentage of land-use observations in the starting period, we are able to use the predicted probability directly to estimate carbon storage and carbon flows based on the coefficient estimates of three separate biometric models. One distinguished feature of this simulation is that it estimates the cost curves by involving all categories of land rather than only concerning forestland. We use agricultural investment as a measure for cost and evaluate impacts of two land policies – *the Basic Farmland Protection Regulation* (hereafter *regulation*) and urban expansion control – on SOC density change.

The procedure is as follows. First, we take data in 2000 as a baseline, predicting land-use change and the associated SOC storage change. Then we generate the first

scenario by ranging RMB ¥50/km^2 increments of agricultural investment on farmland from RMB ¥0/km^2 to RMB ¥1000/km^2. We assess the effects of the “dynamic balance” policy in *the regulation* under scenario 2. In particular, based on scenario 1, we modified the land-use choice model by setting the coefficient of percentage of urbanized farmland to be zero. Therefore this scenario is a package of agricultural investment augment and farmland policy. With a similar strategy we examine the effectiveness of urban development control policy under scenario 3 and scenario 4, under which e restrict urban expansion 20% off and 30% off the baseline, respectively. These two scenarios are a combination of agricultural investment increment and urban land policy.

Figure 2 demonstrates the marginal costs of soil carbon sequestration under scenario 1. The cost curves exhibit great spatial variations in three regions. An increment of agricultural investment on farmland increases SOC storage in inland and south regions. By contrast, increased agricultural investment results in a reduction of SOC density. Besides, the marginal sequestration cost in south area is much higher than that in inland region. For example, an increase in agricultural investment by RMB ¥400/km^2 tends to sequester 0.0003 tons of SOC in south region, while the same amount investment in inland area sequesters 0.0017 tons.

It is not difficult to understand why an increment of agricultural investment decreases SOC storage in the north part. Increased agricultural investment does augment the farmland areas in all three regions as shown in figure 5, which presents a comparison

of land area percent for farmland, forestland, and urbanland with an extra RMB¥1000 agricultural investment. However, in north region, SOC density of farmland is lower than that of urbanland, which produces a downward slope of marginal cost curve in the north region. In this sense, it is more efficient to target at inland area for soil carbon sequestration. We will extend the simulation to three policy scenarios based on this region.

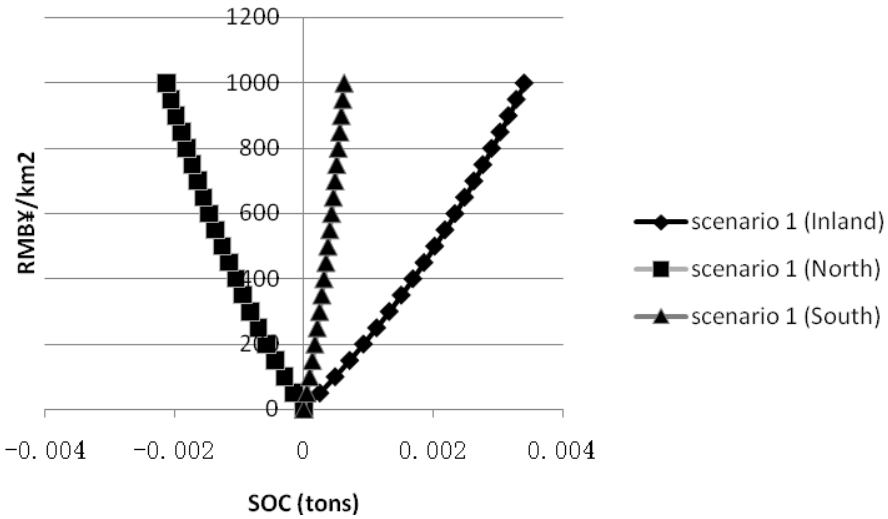

Figure 2. The marginal costs of soil carbon sequestration under scenario 1 in Huang-Huai-Hai Plain

Figure 3a, 3b, and 3c suggest that a land policy package is much more cost-effective than economic incensives alone for soil carbon sequestration. Specifically, if there were no a requirement for "dynamic balance", an extra thousand RMB ¥/km^2 spent on agricultural investment can sequester 0.3794 tons carbon from atmosphere, in contrast to 0.0034 tons carbon in the case with the requirement. Therefore "dynamic balance" exacerbates losses of SOC. A story can be told on farmland protection and urban expansion. In the past decades, China has experienced unprecedented urban expansion,

which is not only driven by fast economic growth, but by local governments. The large number of literature demonstrates that revenue from rural land requisition is an important fiscal source for local governments in China. In this circumstance, the *regulation* plays a real role in ensuring the amount of farmland rather than protecting farmland from converting to urban area. “Dynamic balance” thus becomes a guide for local governments to replace urbanized farmland with other lands. SOC densities of forestland, grassland, and water area are generally higher than that of farmland. Since SOC densities of farmland and urban area are very close, an expansion of urban to farmland results in carbon losses mainly from losses of forestland, grassland, and water area.

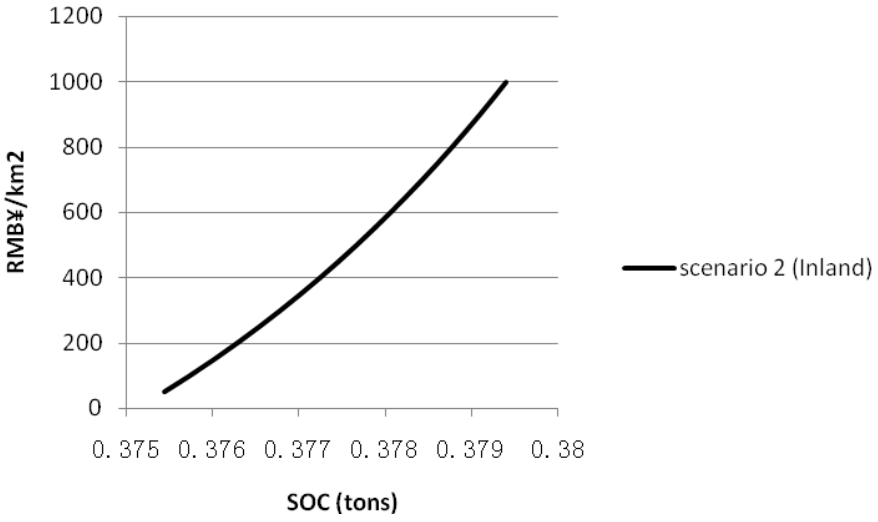

Figure 3a. The marginal costs of soil carbon sequestration under scenario 2 in Inland region

The story by no means indicates that farmland protection makes no sense. In contrast, we emphasize the effectiveness of a land policy. Under scenario 3 and 4, we analyze urban control policy package based on the baseline, i.e. increasing agricultural investment plus restricting urban expansion. In this case, an extra agricultural investment of one

thousand RMB ¥/km^2 can sequester 0.2788 and 0.4144 tons carbon, respectively by bounding the share of urban area 20% off and 30% off the baseline. These results are comparable to that under scenario 2. Figure 5 reports a comparison of percentage of farmland, forestland, and urban land areas among the baseline and three scenarios. In particular, farmland area has the largest percent in scenario 4 and the least one in scenario 2; the percentage of forest land area is the percentage of forest is highest in scenario 4 and lowest under the baseline; while urban area share is largest under the baseline and lowest in scenario 4.

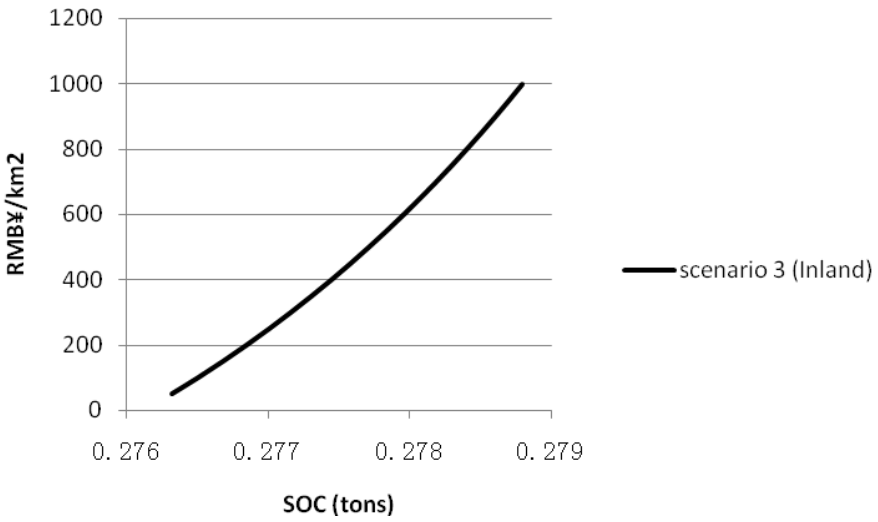

Figure 3b. The marginal costs of soil carbon sequestration under scenario 3 in Inland region

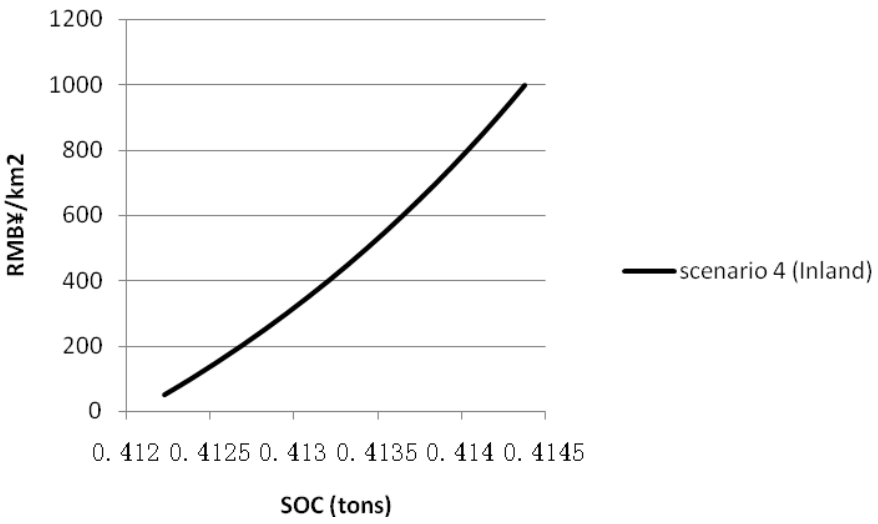

Figure 3c. The marginal costs of soil carbon sequestration under scenario 4 in Inland region

Given the relative positions of the cost curves, the results suggest that soil carbon sequestration merits consideration by combining a policy of urban development control. This policy implication makes sense to the current situation in China. Urban expansion is not equivalent to urbanization. Vernon Henderson has described China's urbanization as "too many city, too few people" in one of his recent reports. High-degree urban expansion, together with low-level urbanization will impair the sustainable development in China. In addition, either land policy or economic incentives should consider a spatial variation issue because the shape of cost curve is sensitive to geographical location.

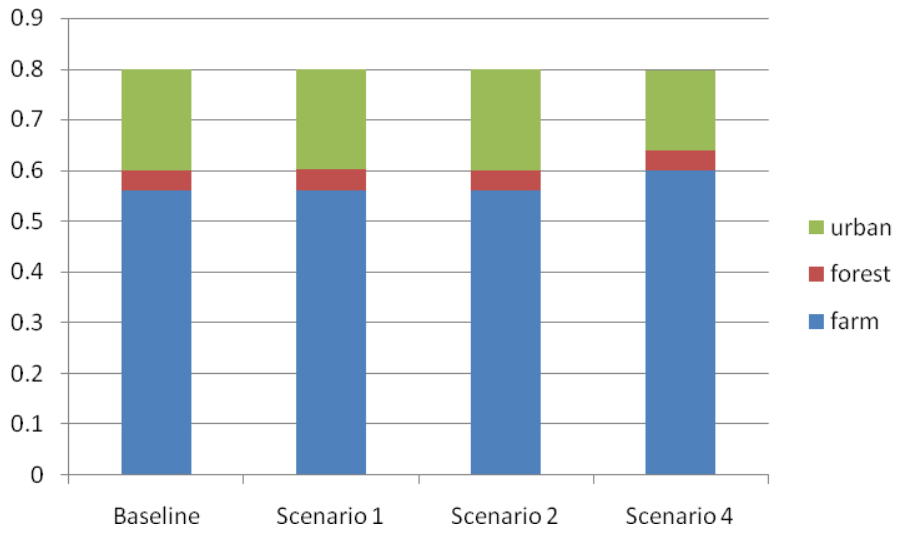

Figure 5. The land area percent of farmland, forestland, and urban area with RMB¥ 1000 extra agricultural investment in Huang-Huai-Hai Plain

Concluding Comments

This paper evaluates the effects of land-use transition on soil carbon storage and sequestration costs in Huang-Huai-Hai Plain of China. We model land-use selection with a discrete choice method among six alternative options. We also conduct a cross-sectional analysis separately on SOC density of three regions. Fine-resolution data of land-use, soil property are employed. We estimate the marginal sequestration costs under several scenarios. A comparison is carried out among three regions, between economic incentives and policy, and within various land policies.

In terms of marginal cost curves, the sign and magnitude of the slope are both sensitive to spatial location. An increment of agricultural investment can increase SOC density in inland and south area. However, the increment make SOC density in north area

declined. In addition, carbon sequestration in inland region is more cost-effective than that in south region. By making a comparison of change in land-use area and SOC storage under three land policy scenarios, we find that the policy of urban expansion control is more environmental friendly.

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References

Adams, Richard M., Darius M. Adams, John M. Callaway, Ching-cheng Chang, and Bruce A. McCarl. "Sequestering Carbon on Agricultural Land: Social Cost and Impacts on Timber Markets." *Contemporary Policy Issues* 11, no. 1 (1993): 76-87.

Alig, Ralph, Darius M. Adams, Bruce A. McCarl, John M. Callaway, and Steven Winnett. "Assessing Effects of Mitigation Strategies for Global Climate Change with an Intertemporal Model of the U.S. Forest and Agriculture Sectors." *Environmental and Resource Economics* 9, no. 3 (1997): 259-74.

Antle, John M., Susan M. Capalbo, Keith Paustian, and Md Kamar Ali. "Estimating the Economic Potential for Agricultural Soil Carbon Sequestration in the Central United States Using an Aggregate Econometric-Process Simulation Model." *Climatic Change* 80, no. 1-2 (2007): 145-71.

Antle, John M., and Bocar Diagana. "Creating Incentives for the Adoption of Sustainable Agricultural Practices in Developing Countries: The Role of Soil Carbon Sequestration." *American Journal of Agricultural Economics* 85, no. 5 (2003): 1178-84.

Capalbo, Susan M., John M. Antle, Sian Mooney, and Keith Paustian. "Sensitivity of Carbon Sequestration Costs to Economic and Biological Uncertainties." *Environmental Management* 33, no. S1 (2004): S238-S51.

Capozza, Dennis R., and Robert W. Helsley. "The Stochastic City." *Journal of Urban Economics* 28, no. 2 (1990): 187-203.

Capozza, Dennis R., and Yuming Li. "The Intensity and Timing of Investment: The Case of Land." *The American Economic Review* 84, no. 4 (1994): 889-904.

Cho, Seong-Hoon, JunJie Wu, and William G. Boggess. "Measuring Interactions among Urbanization, Land Use Regulations, and Public Finance." *American Journal of Agricultural Economics* 85, no. 4 (2003): 988-99.

Deng, Xiangzheng, Jikun Huang, Scott Rozelle, and Emi Uchida. "Cultivated Land Conversion and Potential Agricultural Productivity in China." *Land Use Policy* 23 (2006): 372-84.

———. "Growth, Population and Industrialization, and Urban Land Expansion of China." *Journal of Urban Economics* 63, no. 1 (2008): 96-115.

Ding, Chengri. "Land Policy Reform in China: Assessment and Prospects." *Land Use Policy* 20, no. 2 (2003): 109-20.

———. "Policy and Praxis of Land Acquisition in China." *Land Use Policy* 24, no. 2 (2007): 1-13.

Fang, Jingyun, Anping Chen, Changhui Peng, Shuqing Zhao, and Longjun Ci. "Changes in Forest

Biomass Carbon Storage in China between 1949 and 1998." *Science* 292, no. 5525 (2001): 2320-22.

Feng, Hongli, Lyubov A. Kurkalova, Catherine L. Kling, and Philip W. Gassman. "Environmental Conservation in Agriculture: Land Retirement Vs. Changing Practices on Working Land." *Jjournal of Environmental Economics and Management* 52, no. 2 (2006): 600-14.

Huang, Yao, and Wenjuan Sun. "Changes in Topsoil Organic Carbon of Croplands in Mainland China over the Last Two Decades." *Chinese Science Bulletin* 51, no. 15 (2006): 1785-803.

Hartkamp, A. D., K. De Beurs, A. Stein and J.W. White. (1999). "Interpolation Techniques for Climate Variables." *NRG-GIS Series* 99-01.

Jobbágy, Esteban G., and Robert B. Jackson. "The Vertical Distribution of Soil Organic Carbon and Its Relation to Climate and Vegetation." *Ecological Applications* 10, no. 2 (2000): 423-36.

Kravchenko, A. and D. G. Bullock (1999). "A comparative study of interpolation methods for mapping soil properties." *Journal of Agronomy* 91: 393–400.

Lal, R. "Soil Carbon Sequestration to Mitigate Climate Change." *Geoderma* 123 (2004): 1-22.

Lewis, David J., and Andrew J. Plantinga. "Policies for Habitat Fragmentation: Combining Econometrics with Gis-Based Landscape Simulations." *Land Economics* 83, no. 2 (2007): 109-27.

Lichtenberg, Erik, and Chengri Ding. "Assessing Farmland Protection Policy in China." *Land Use Policy* 25, no. 1 (2008): 59-68.

Lin, George C.S, and Samuel P.S Ho. "China's Land Resources and Land-Use Change: Insights from the 1996 Land Survey." *Land Use Policy* 20, no. 2 (2003): 87-107.

Liu, J. Y., M. L. Liu, D. F. Zhuang, Z. X. Zhang and X. Z. Deng (2003). "Study on spatial pattern of land-use change in China during 1995-2000." *Science in China D-Earth Sciences* 46(4): 373-384.

Lubowski, Ruben N., Andrew J. Plantinga, and Robert N. Stavins. "Land-Use Change and Carbon Sinks: Econometric Estimation of the Carbon Sequestration Supply Function." *Journal of Environmental Economics and Management* 51, no. 2 (2006): 135-52.

Marland, Gregg, Tom Boden, and Robert J. Andres. "National Co_2 Emissions from Fossil-Fuel Burning, Cement Manufacture, and Gas Flaring: 1751-2004." edited by Oak Ridge National Laboratory Carbon Dioxide Information Analysis Center, U.S. Department of Energy. Oak Ridge Tennessee, 2007.

Parks, Peter J., and Ian W. hardie. "Least-Cost Forest Carbon Reserves: Cost-Effective Subsidies to Convert Marginal Agricultural Land to Forests." *Land Economics* 71, no. 1 (1995): 122-36.

Parton, W.J., J.M.O. Scurlock, D.S. Ojima, T.G. Gilmanov, R.J. Scholes, D.S. Schimel, T. Kirchner, J-C. Menaut, T. Seastedt, E. Garcia Moya, Apinan Kamnalrut, and Kinyamario J.I. "Observations and Modeling of Biomass and Soil Organic Matter Dynamics for the Grassland Biome Worldwide." *Global Biogeochemical Cycles* 7, no. 4 (1993): 785-809.

Plantinga, Andrew J., Ruben N. Lubowski, and Robert N. Stavins. "The Effects of Potential Land Development on Agricultural and Land Prices." *Journal of Urban Economics* 52 (2002): 561-81.

Plantinga, Andrew J., Thomas Mauldin, and Douglas J. Miller. "An Econometric Analysis of the Costs of Sequestering Carbon in Forests." *American Journal of Agricultural Economy* 81, no. 4

(1999): 812-24.

Polyakov, Maksym, and Daowei Zhang. "Property Tax Policy and Land-Use Change." *Land Economics* 84, no. 3 (2008): 396-408.

Qu, Futian, Nico Heerink, and Wanmao Wang. "Land Administration Reform in China." *Land Use Policy* 12, no. 3 (1995): 193-203.

Richards, Kenneth R., and Carrie Stokes. "A Review of Forest Carbon Sequestration Cost Studies: A Dozen Years of Research." *Climatic Change* 63, no. 1-2 (2004): 1-48.

Schlesinger, William H. "Carbon Balance in Terrestrial Detritus." *Annual Review of Ecology and Systematics* 8 (1977): 51-81.

Schlesinger, William H., and Jeffrey A. Andrews. "Soil Respiration and the Global Carbon Cycle." *Biogeochemistry* 48, no. 1 (2000): 7-20.

Seto, Karen C., and Robert K. Kaufmann. "Modeling the Drivers of Urban Land Use Change in the Pearl River Delta, China: Intergating Remote Sensing with Socioeconomic Data." *Land Economics* 79, no. 1 (2003): 106-21.

Shi,,Y.C. Comprehensive reclamation of salt-affected soils in China's Huang-Huai-Hai Plain. In: S.S. Goyal, S.K. Sharma and D.W. Rains, Editors, *Crop Production in Saline Environments: Global and Integrative Perspectives*, Food Products Press, an Imprint of the Haworth Press, Inc., New York (2003), pp. 163–179.

Stavins, Robert N. "The Costs of Carbon Sequestration: A Revealed-Preference Approach." *The American Economic Review* 89, no. 4 (1999): 994-1009.

Tan, Minghong, Xiubin Li, Hui Xie, and Changhe Lu. "Urban Land Expansion and Arable Land Loss

in China -- a Case Study of Beijing-Tianjin-Hebei Region." *Land Use Policy* 22, no. 3 (2005): 187-96.

Tang, Huajun, Jianjun Qiu, Eric Van Ranst, and Changsheng Li. "Estimations of Soil Organic Carbon Storage in Cropland of China Based on Dndc Model." *Geoderma* 134, no. 1-2 (2006): 200-06.

Wang, C., H. Ouyang, W. Maclaren, Y. Yin, B. Shao, A. Boland, and Y. Tian. "Evaluation of the Economic and Environmental Impact of Converting Cropland to Forest: A Case Study in Dunhua County, China." *Journal of Environmental Management* 85, no. 3 (2007): 746-56.

Wang, Shaoqiang, Mei Huang, Xuemei Shao, Robert A. Mickler, Kerang Li, and Jingjun Ji. "Vertical Distribution of Soil Organic Carbon in China." *Environmental Management* 33, no. S1 (2004): S200-S09.

Wang, Shaoqiang, Hanqin Tian, Jiyuan Liu, and Shufen Pan. "Pattern and Change of Soil Organic Carbon Storage in China: 1960s-1980s." *Tellus* 55B, no. 2 (2003): 416-27.

Wu, Haibin, Zhengtang Guo, and Changhui Peng. "Distribution and Storage of Soil Organic Carbon in China." *Global Biogeochemical Cycles* 17, no. 2 (2003): 1-11.

Wu, JunJie, Richard M. Adams, Catherine L. Kling, and Katsuya Tanaka. "From Microlevel Decisions to Landscape Changes: An Assessment of Agricultural Conservation Policies." *American Journal of Agricultural Economics* 86, no. 1 (2004): 26-41.

Wu, JunJie, and Seong-Hoon Cho. "The Effect of Local Land Use Regulations on Urban Development in the Western United States." *Reginal Science and Urban Economics* 37, no. 1 (2007): 69-86.

Xu, DeYing. "The Potential for Reducing Atmospheric Carbon by Large-Scale Afforestation in China

and Related Cost/Benefit Analysis." *Biomass and Bioenergy* 8, no. 5 (1995): 337-44.

Yang, H.S. and B.H. Janssen, Analysis of impact of farming practices on dynamics of soil organic matter in northern China, *Eur. J. Agron.* **7** (1997), pp. 211–219.

Yang, Yuanhe, Anwar Mohammat, Jianmeng Feng, Rui Zhou, and Jingyun Fang. "Storage, Patterns and Environmental Controls of Soil Organic Carbon in China." *Biogeochemistry* 84 (2007): 131-41.

Zhang, F., Changsheng Li, Z. Wang, and Haibin Wu. "Modeling Impacts of Management Alternatives on Soil Carbon Storage of Farmland in Northwest China." *Biogeosciences* 3 (2006): 451-66.

Zhou, S, Y. Yin, W. Xu, Z. Ji, I. Caldwell, and J. Ren. "The Costs and Benefits of Reforestation in Liping County, Guizhou Province, China." *Journal of Environmental Management* 85, no. 3 (2007): 722-35.