Landscape and Urban Planning 108 (2012) 131–139

Contents lists available at SciVerse ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research paper

Multi-level modeling of urban expansion and cultivated land conversion for urban hotspot counties in China

Li Jiang[a,*], Xiangzheng Deng[b], Karen C. Seto[a]

[a] Yale School of Forestry and Environmental Studies, Yale University, 195 Prospect Street, New Haven, CT 06511, USA
[b] Center for Chinese Agricultural Policy, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

HIGHLIGHTS

- We examine the urban conversion of cultivated land in China at the national scale.
- Our model takes account of the decentralized nature of China's urbanization.
- Overall local factors play a dominant role in determining urban expansion.
- Agricultural investment drives farmland conversion, suggesting a policy failure.
- We identify a boosting mechanism between urban land rent and urban development.

ARTICLE INFO

Article history:
Received 1 November 2011
Received in revised form 28 August 2012
Accepted 31 August 2012
Available online 23 September 2012

Keywords:
Urbanization
Farmland loss
Urban land-use change
County and provincial levels
Socioeconomic factors
Longitudinal data

ABSTRACT

China has undergone large-scale urban expansion and rapid loss of cultivated land for more than two decades. The goal of this paper is to examine the relative importance of socioeconomic and policy factors across different administrative levels on urban expansion and associated cultivated land conversion. We conduct the analysis for urban hotspot counties across the entire country. We use multi-level modeling techniques to examine how socioeconomic and policy factors at different administrative levels affect cultivated land conversion across three time periods, 1989–1995, 1995–2000, and 2000–2005. Our results show that at the county level, both urban land rent and urban wages contribute to total cultivated land conversion. Contrary to expectations, agricultural investment drives farmland conversion, suggesting a policy failure with unintended consequences. At the provincial level, urban wages and foreign direct investment both positively contribute to cultivated land conversion. We also find that higher GDP correlates with more urban expansion but the relationship is nonlinear.

Published by Elsevier B.V.

1. Introduction

The current demographic transition in China is one of the largest in the world in terms of the scale of urban population growth (Chuang-lin, 2009; Pannell, 2002). The proportion of urban population increased to 47% in 2010 from 22.9% in 1985. This trend is expected to continue, with a projected 270 million increase in China's urban population over the next two decades (United Nations, 2009). This urban demographic shift has been accompanied with large-scale urban land expansion and the resultant loss of agricultural land throughout the country (Seto, Kaufmann, & Woodcock, 2000; Tan, Li, Xie, & Lu, 2005; Wang & Scott, 2008). Nationwide, the urban extent increased by 817 thousand ha during the 1990s, or an area roughly equal in size to Puerto Rico (Liu, Zhan, & Deng, 2005). Official statistics and calculations derived from satellite imagery show that urban development occurred on more than 334 thousand ha of cultivated land between 1986 and 2003, accounting for 21% of the total loss of cultivated land (Chen, 2007). This is more prominent in regions that have experienced rapid economic growth and urban development, such as the Pearl River Delta and Beijing-Tianjin-Hebei regions (Seto & Kaufmann, 2003; Tan, Li, Xie, et al., 2005). A study of 145 Chinese cities shows that urban growth during the 1990s took place primarily on cultivated land (Tan, Li, & Lu, 2005). Although the central government has introduced a number of policies aimed at cultivated land preservation, including the Basic Farmland Protection Regulation enacted in1994 and the 1999 New Land Administration Law, losses of cultivated land are still taking place, particular in the coastal and central provinces (Lichtenberg & Ding, 2008). In addition to the direct loss of cultivated due to urban expansion, a substantial change in dietary patterns, including a decrease in the consumption of food grains and a rise in the consumption of egg, milk and livestock products, puts additional pressure on the country's cultivated

* Corresponding author. Tel.: +1 203 909 0184; fax: +1 203 432 5556.
E-mail addresses: li.jiang@yale.edu (L. Jiang), dengxz.ccap@igsnrr.ac.cn (X. Deng), karen.seto@yale.edu (K.C. Seto).

0169-2046/$ – see front matter. Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.landurbplan.2012.08.008

land and production (Pingali, 2007). The combination of continued growth of Chinese cities, limited arable land, and changes in the composition of domestic food demand puts existing cultivated land at risk for conversion to urban areas, and natural ecosystems at risk for conversion to farmland. Therefore, an understanding of the relationship between urban expansion and cultivated land loss is critical in order to achieve the twin goals of urban growth and preservation of farmland and natural ecosystems.

Despite the magnitude and pace of urban expansion across the country, there is limited understanding about the patterns and the underlying processes of urban land use change at the national scale. Most of the research on urban expansion in China has been devoted to studying the growth of individual cities or regions (Cheng & Masser, 2003; He, Okada, Zhang, Shi, & Li, 2008; Long, Tang, Li, & Heilig, 2007; Schneider, Seto, & Webster, 2005). Among the studies at the national scale (Deng, Huang, Rozelle, & Uchida, 2008; Deng, Huang, Rozelle, & Uchida, 2010; Liu, Liu, Deng, Zhang, & Zhuang, 2003; Tan, Li, & Lu, 2005), very few studies explain the process of urban expansion using systematic methods and none quantitatively examines the urban conversion of cultivated land. Unlike the previous studies looking at the spatial extent of cities, we directly investigate the mechanism of the area of land conversion. Furthermore, to our knowledge, no study simultaneously takes into consider the legalization of the land leasing market, urban planning policies, and the increasingly decentralized and unstructured nature of China's urban development. Policies at various administrative levels have exerted fundamental influences on the magnitude, the pattern, and the process of urban expansion. However, to date, there have been no empirical studies that incorporate these factors across administrative levels explicitly.

This study examines the relative importance of socioeconomic factors and policies at different administrative levels in driving the conversion of cultivated land in regions characterized by rapid urban growth. We focus specifically on "urban hotspot counties," defined as counties that experienced urban land expansion faster than the remainder of the country. Using a multi-level modeling approach, we ask the following questions. What county-level factors drive the urban conversion of cultivated land in urban hotspot counties? What provincial-level factors drive the urban conversion of cultivated land? What national-level factors drive the urban conversion of cultivated land? What is the relative importance of these factors across administrative levels? As a national level research, the study is useful in reflecting the broad picture of the urbanization process in China, but the underlying mechanism derived is based on and limited to the urban hotspot counties.

2. Literature review on theories of urban land-use change and multi-level modeling in land use

We use two categories of theories to frame our study of urban expansion and cultivated land loss: the microeconomic theory of land use change (Bockstael, 1996; Rosenthal & Helsley, 1994) and the urban bid-rent model (Beckmann, 1969; Von Thunen, 1826).

The microeconomic theory of land use change views the urban development of agricultural land as the outcome of decisions from individual land users, who attempt to maximize the expected profits of individual parcels. Spatially-explicit models based on microeconomic theory are useful in understanding the spatial and temporal dynamics of land use decisions among individual agents, but they do not provide information about the cumulative amount of land change (Verburg, Schot, Dijst, & Veldkamp, 2004). Further, these land use models do not account for the complexities of institutional and socioeconomic settings that are exogenous to the micro-environment of individual land users.

The bid-rent model, as the basis of urban economic theory, explains the accumulated outcome of urban land use change. It theoretically defines the distance to a city center as the single determinant of land rents and the resulting distribution of land uses. Later scholars expanded the bid-rent model, incorporating the influence of income (Barlowe, 1978), improved transportation (White, 1988), and spatial heterogeneities in terms of soil quality, climate, natural resource endowments, etc. (Moses & Williamson, 1967). Under the frame of the bid-rent model, aspatial land use models have been developed and empirically tested with the objective to understand the spatial scale of cities (Brueckner & Fansler, 1983; McGrath, 2005), industrialization and urban land expansion (Deng et al., 2008, 2010), and urbanization and the conversion of agricultural land and natural land covers (Seto & Kaufmann, 2003). Using 1970 census data for 40 urbanized areas in the U.S., Brueckner and Fansler found that the fundamental economic factors identified by the bid-rent model, population, income, transportation costs and agricultural land rent, are of primary importance in determining urban spatial sizes. McGrath's results reinforced Brueckner and Fansler's conclusion, and recognized that unknown factors beyond those identified by the bid-rent model also contribute to urban expansion.

The presence of these unknown factors means that the bid-rent model can only explain the increase of urban areas to certain extent. In the case of China, where the land market has not matured and state allocation of land still remains the dominant way of distributing land use rights, there are additional reasons why the bid-rent model may be limited. Researchers have highlighted the role of policies and the shifts of macroeconomic environments on urban land-use change in China, including the importance of foreign direct investment and off-farm wages (Seto & Kaufmann, 2003), the relaxation of the "*hukou*" system of residency permits (Shen, Wong, & Feng, 2002; Xie, Fang, Lin, Gong, & Qiao, 2007), and governance decentralization and the profit-seeking behaviors of various local agents (Wang & Scott, 2008). There are only a few national-scale studies on urban land-use change and farmland conversion in China. Using counties as the analytical unit, Deng et al. (2008, 2010) evaluate the demographic and economic factors that drive urban expansion. Their results support the key hypotheses of the bid-rent model, and emphasize the impacts of rising income and industrialization on urban growth. Since the focus of their studies is on the change in urban spatial size, limited conclusions can be made about the loss of cultivated land due to urbanization. Moreover, their study design only includes factors that drive urban growth at the county level and ignore regional level factors.

More than two decades of land change research concludes that land use changes are the outcomes of biophysical and socioeconomic determinants that occur across multiple spatial and temporal scales (Geoghegan & Pritchard, 1998). In order to capture and represent these effects, we use a multi-level modeling approach, which is capable of integrating variation that originate from multiple scales and levels to evaluate the relative impact of policies and factors across administrative and spatial scales. Multi-level modeling is particularly suited to analyze land-use data with spatially clustered hierarchical structure (Gelman & Hill, 2007; Snijders & Bosker, 1999). There are only a few examples of multi-level modeling in land-use studies. Multi-level models outperform conventional regression models in handling hierarchically structured data in many perspectives: they treat within-group variation and between-group variation separately, hence minimizing the problems of inefficient parameter estimates and understated standard error estimates resulting from the within-group dependence associated with hierarchical data (Overmars & Verburg, 2006; Snijders & Bosker, 1999); they reduce omitted variable bias by incorporating covariates and random effects at the group level to control for spatial heterogeneity; they not only take account of the

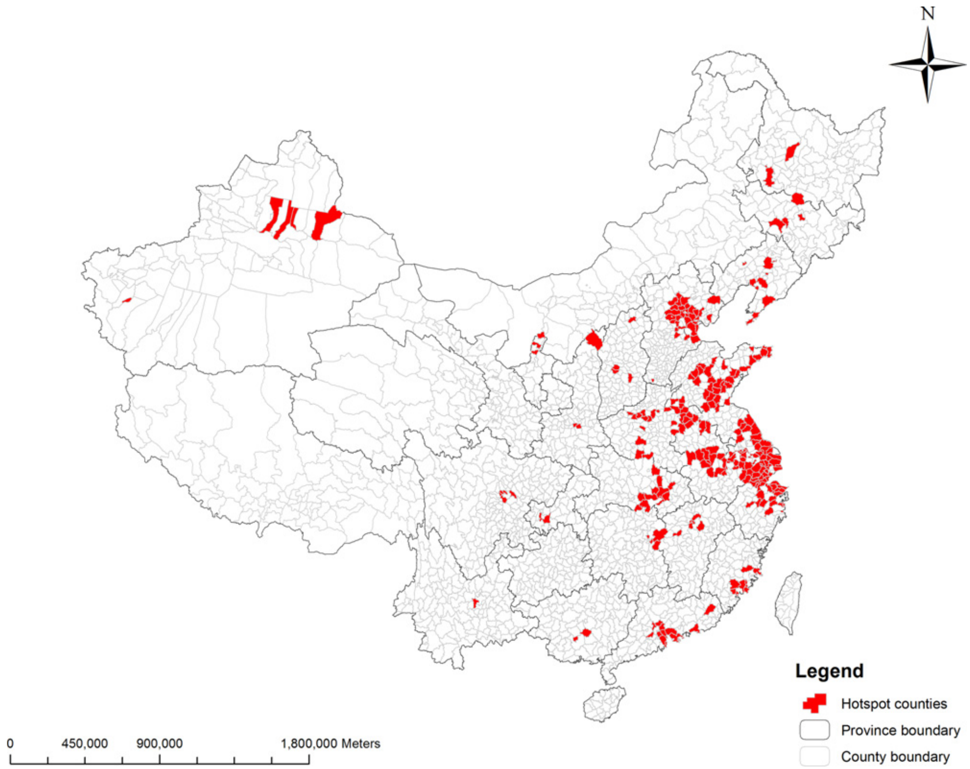

Fig. 1. Urban hotspot counties between 1992 and 2008.

direct trajectory by which higher-level driving factors affect the land use, but the indirect trajectory by which higher-level factors influence the land use via lower levels (Hoshino, 2001). Among the few studies of multi-level modeling of land use (Overmars & Verburg, 2006; Pan & Bilsborrow, 2005; Vance & Iovanna, 2006), only Vance and Iovanna (2006) use longitudinal data. There are more methodological challenges with respect to analyzing longitudinal land use data using multi-level modeling techniques (Bliese, 2002). In the case of longitudinal data, repeat observations about land use change from a spatial entity (such as community) represent the first level in the hierarchy, and the spatial entity itself represents the second level. If the spatial entity is nested within other higher-level spatial entities (such as municipality and state), higher-level random effects and covariates can be incorporated and specified accordingly in the multi-level model.

3. Urban expansion datasets: identifying urban hotspots and developing a national database of urban expansion

We used a 2-stage process to identify urban hotspots and the urban expansion within them. We define urban hotspots as counties that experienced higher rates of urban growth—as detected by the nighttime light (NTL) data recorded by the U.S. Air Force Defense Meteorological Satellites Program/Operational Linescan system (DMSP/OLS)—relative to neighboring counties from 1992 to 2008. The nighttime light data is a measure of night light intensity, and has been shown to be an indicator of urban activities (Doll, Muller, & Morley, 2006; Sutton & Costanza, 2002; Zhang & Seto, 2011). Using the DMSP/OLS data, we conducted a Local Indicators of Spatial Association (LISA) analysis, a spatial analytical technique for identifying the presence or absence of spatial clusters (Anselin, 1995). We conducted the LISA analysis at the county level to identify urban cluster hotspots for four time intervals: 1992–1996, 1996–2000, 2000–2004 and 2004–2008.

For each time interval, the analysis consisted of three steps: First, we overlaid the DMSP/OLS raster file for each of the two observation years with the county's administrative polygon shapefile and calculated the total sum of the DMSP/OLS values for each polygon for each year. Second, we generated a difference map between the two observation years. Third, the difference map was used to calculate hotspots maps based on the LISA algorithm (Anselin, Syabri, & Kho, 2006). We then combined the four sets of urban hotspots detected for each time interval to create a complete list of urban hotspots between 1992 and 2008 (Fig. 1). This list, which consisted of 246 urban hotspot counties distributed in 25 provinces, was used in the next stage to compare with the national data set on urban land expansion.

Since understanding the underlying process that drives urban expansion and agricultural land conversion is the main goal of the study, we require high resolution, spatially explicit data on land-use change. Aggregated land use data that are available in provincial or prefectural statistical year books lack the adequate temporal and spatial resolution for our study. Moreover, land use data published by the Chinese government have been questioned for underestimating the quantity of agricultural land and its rate of loss (Chow, 1994; Seto et al., 2000).

Therefore, we used a land use data set that were derived from the NASA Landsat TM/ETM satellite, and analyzed by the Chinese Academy of Sciences (CAS) (Liu, Liu, Deng, & Zhuang, 2002; Liu et al., 2003). This national data set, which has undergone extensive testing and development, contains spatially explicit information about the extent of urban and cultivated land for the years 1989, 1995, 2000, and 2005. Using data from these years as baselines, we calculated the amount of cultivated land loss due to urban expansion for the periods 1989–1995, 1995–2000, and 2000–2005, and then combined this data set with the list of urban hotspot counties developed from the LISA analysis. Nationwide, the land use data for year 1989 were derived from satellite images across 1986–1989. However, with a careful check of the data, we find that regions identified as the urban hotspots are mainly covered by images in 1989. So the data set that we use to combine with the list of urban hotspot counties basically captures the land use change information during 1989–1995. Later we defined the time variable to represent the three periods of the data set. The multi-level modeling approach can only capture variations in the conversion of cultivated land between different time periods. Understanding variations in the conversion of cultivated land within particular period requires more data and additional future research.

We hypothesize that the conversion of cultivated land for urban uses is due to the effects of two key determinants of urban extent in the bid-rent model (land rents and income) and several other important socioeconomic factors documented in empirical studies (off-farm wages, agricultural investments, and foreign direct investments). We used data on total and sector gross domestic product (GDP) at the county and provincial levels, total and agricultural population at the county and provincial levels, and provincial foreign direct investment as measures to test the aforementioned hypotheses. All the data were collected by the CAS.

We included a set of biophysical variables in our analysis in order to capture natural geographic variation across space. We intend to test how county's relative location, terrain and climate characteristics affect urban expansion and cultivated land loss. The data reflecting terrain attributes were generated from China's digital elevation model data set by the CAS. The distance of each county seat to the provincial capital was calculated by Deng and his colleagues using data from the CAS data center (Deng, Liu, Zhan, & Zhao, 2002; Deng et al., 2010). The climate data are created by Deng and his colleagues using the site-based observations from the China Meteorological Administration from 1950 to 2000. The socioeconomic and biophysical data sets were also combined with the list of urban hotspot counties.

4. Multi-level models and variable specifications

We followed guidelines from the literature on multi-level modeling and applied a restricted maximum likelihood (RML) algorithm for our model estimation (Osgood & Smith, 1995; Snijders & Bosker, 1999). In the multi-level models, our dependent variable is *ConvertedLand*, the amount of cultivated land that in a county has been converted to urban uses for each of the three time intervals: 1989–1995, 1995–2000 and 2000–2005. Time is represented by *Year*, with 0 for 1989, 6 for 1995 and 11 for 2000. The bid-rent model suggests that land rents and income are important determinants of urban extent. At the same time, empirical studies report that off-farm wages, agricultural investments, and foreign direct investments are important factors that drive urban expansion in China. Combining these two arguments, we select three socioeconomic variables at the county level and three socioeconomic variables at the province level. Specifically, *LandRentRatio* is defined as the ratio between agricultural land rent and urban land rent in a county for a given year (1989, 1995 or 2000).

The conversion of cultivated land to urban land is affected by land rents and land prices associated with individual land uses. Since there is no consistent information about land rent across Chinese counties, we use the value of gross agricultural output divided by cultivated land area as a proxy for agricultural land rent and the value of gross industrial output divided by urban land area a proxy for urban land rent (Seto & Kaufmann, 2003). *UrbWage*, is the urban wage as specified by the ratio of the value of gross industrial output over the nonagricultural population for a county in a given year (1989, 1995 or 2000). High urban wages are expected to increase the opportunity costs of farming, and result in labor scarcity in the agricultural sector (Conelly, 1994). *AgriInvest* represents the agricultural investments per capita in a county for a given year (1989, 1995 or 2000). Agricultural investments from the national and provincial governments which are allocated at the county scale are aimed at enhancing agricultural productivity and promoting agricultural economic development and farmland preservation. *GDP_p* is the gross domestic output of a province for a given year (1989, 1995 or 2000) and is used as an indication of population income for the region. *UrbWage_p* is defined similarly to *UrbWage*, but is a measurement at the provincial level. Studies of migration to cities show that the pull effect of urban wages exists at both the local and regional scales. *FDI_p* represents foreign direct investments (FDI) per capita of a province for years 1989, 1995 or 2000. Many scholars have emphasized the role of FDI in funding the regional infrastructures, real estate projects, and light industries during the process of China's economic development (Eng, 1997; Houkai, 2002). Since spatial heterogeneities and locational advantages affect urban growth, a group of biophysical variables, which do not vary over time, are specified and used to control for time-invariant spatial heterogeneities. *DistPCapit* measures the distance from the county seat to the provincial capital and it provides information about the county's relative location. *PlainRatio* is the ratio of land with a slope less than eight degrees in a county and *Elevation* represents average elevation of a county. Together, they measure the average terrain condition or suitability for urban construction. *Precipitation*, which is the average annual precipitation in a county, and *Temperature*, which is the average annual air temperature in a county, are controls for geographic and climate characteristics (Table 1).

We followed steps suggested in the literature to build a series of multi-level models and to select the optimum one as the base model for including explanatory variables. First, we fit a model with the county-level random intercepts only (assuming the response randomly varies among counties) and examine the form of the relationship between time and the response. Next, we examined whether the response randomly varies among provinces and whether the relationship between time and the response varies among counties. In this step, we use univariate tests of the individual variance components and multivariate tests of overall model fit in order to select the optimum model. In the third and final step, we added predictors at different administrative levels to the base model.

For all multi-level models definitions in the remainder of the paper, we use the following notation: *i* indexes counties, *t* indexes time and *j* indexes provinces. We start by fitting two basic multi-level models, with the purpose of identifying the correct form of the relationship between time and the response. These models can be regarded as the unconditional models since no explanatory variables other than the time variables are incorporated.

$$Log(ConvertedLand)_{it} = \beta_0 + \beta_1 Year_{it} + u_{0i} + \varepsilon_{it} \quad (1)$$

In Eq. (1), u_{0i} is the random intercept that varies randomly between counties and is assumed to be normally distributed with a zero mean and a variance of τ_0^2. ε_{it} is the error term which is normally distributed with a zero mean and a variance of σ^2. β_0 and β_1 are regression coefficients to be estimated.

$$Log(ConvertedLand)_{it} = \beta_0 + \beta_1 Year_{it} + \beta_2 Year_{it}^2 + u_{0i} + \varepsilon_{it} \quad (2)$$

In Eq. (2), a squared term of *Year* is added and the other parts remain the same as Eq. (1). The estimation results of Eqs. (1) and (2) indicate that both linear and quadratic effects of time are significant. As a consequence, both time effects have to be incorporated when estimating our multi-level models.

Next, we determined the optimum number and form of random effects that are adequate for the multi-level model. We assume that the response randomly varies among counties, but the response could vary randomly among provinces and that the relationship

Table 1
Variables used in the study.

Variable	Description
Dependent variable	
ConvertedLand	Area of land converted from agriculture to urban uses in a county within 1989–1995, 1995–2000, or 2000–2005 intervals (ha)
Independent variables	
County level	
Year	Variable for time (0 for year 1989, 6 for year 1995 and 11 for year 2000)
LandRentRatio	$\frac{\text{GDP in agricultural sector/area of agricultural land (in a county)}}{\text{GDP in industrial sector/area of urban land (in a county)}}$ (%)
UrbWage	$\frac{\text{GDP in industrial sector (in a county)}}{\text{nonagricultural population (in a county)}}$ (10 thousand yuan)
AgriInvest	Agricultural investment per capita (yuan)
DistPCapit	Distance from the county seat to the provincial capital (m)
PlainRatio	Ratio of land with a slope less than eight degrees in a county (%)
Elevation	Average elevation of a county (m)
Precipitation	Average annual precipitation in a county (mm)
Temperature	Average annual air temperature in a county (°C)
Province level	
GDP_p	GDP of a province (10 thousand yuan)
UrbWage_p	$\frac{\text{GDP in industrial sector (in a province)}}{\text{nonagricultural population (in a province)}}$ (10 thousand yuan)
FDI_p	Foreign direct investment per capita (10 thousand yuan)

1 Chinese yuan ≈ 0.1574 US dollars.

Table 2
Unconditional models for the stage of model selection.

	Dependent variable: *Log*(*ConvertedLand*)			
	Eq. (1)	Eq. (2)	Eq. (3)	Eq. (4)
Intercept	5.594 (0.096)*	5.998 (0.093)*	5.909 (0.147)*	5.909 (0.147)*
Year	0.025 (0.011)*	−0.458 (0.033)*	−0.458 (0.033)*	−0.458 (0.033)*
Year^2		0.045 (0.003)*	0.045 (0.003)*	0.045 (0.003)*

* $p < 0.05$.

between time and the response varies among counties. In order to test for this, we develop variations of Eq. (2). Eq. (3) has two random effects: a county-level random intercept u_{0ij} and a province-level random intercept v_{0j}, both of which are assumed to be independently normally distributed. Eq. (4) has three random effects: a county-level random intercept u_{0i}, a county-level random slope u_{1i} interacted with time, and a province-level random intercept v_{0j}, where u_{0ij} and u_{1ij} are assumed to be multivariate normally distributed and v_{0j} is assumed to be independently normally distributed (Table 2).

$$Log(ConvertedLand)_{ijt} = \beta_0 + \beta_1 Year_{ijt} + \beta_2 Year_{ijt}^2 + u_{0ij} + v_{0j} + \varepsilon_{ijt} \quad (3)$$

$$Log(ConvertedLand)_{ijt} = \beta_0 + \beta_1 Year_{ijt} + \beta_2 Year_{ijt}^2 + u_{0ij} + u_{1ij} Year_{ijt} + v_{0j} + \varepsilon_{ijt} \quad (4)$$

Eq. (3) examines the intercept variability at the county and province levels. The variance of between-county intercepts σ_u^2 and the variance of between-province intercepts σ_v^2 are 0.639 and 0.268 respectively ($p < 0.001$ for both), indicating significant between-group variations at the county and province levels. Further, as Eqs. (2) and (3) are nested, we conduct a likelihood ratio test by calculating the difference in the deviance statistic between the two equations (Bliese, 2002; Vance & Iovanna, 2006). The difference of 20.7 is significant on a Chi-Squared distribution with one degree of freedom ($p < 0.0001$), providing clear evidence for an improvement of model fit in Eq. (3). Eq. (4) tests the county slope variability relative to Eq. (3). However, the variance of the random slope is not significant and the result of likelihood ratio test does not show a significant improvement in overall fit. These results suggest that there is not significant county slope variation. Considering that our data structure is characterized by the observations of 250 counties nested within 25 provinces, the relative small sample size may hamper the estimation of random slopes. Our experience is similar to that of previous studies which also identified insignificant random slopes (Overmars & Verburg, 2006; Polsky & Easterling, 2001). Given the above reasons, we choose Eq. (3), which allows converted cultivated land to randomly vary among both counties and provinces, as our base model (Model 1) for including explanatory variables at different administrative levels.

To estimate the effects of socioeconomic factors at different administrative levels on urban expansion and agricultural land loss, we sequentially added three sets of explanatory variables to the base model (Model 2–Model 4):

$$Log(ConvertedLand)_{ijt} = \beta_0 + \beta_1 Year_{ijt} + \beta_2 Year_{ijt}^2 + \sum_{p=1}^{P} \alpha_p X_{pijt} + \sum_{q=1}^{Q} \lambda_q X_{qij} + \sum_{r=1}^{R} \gamma_r Z_{rjt} + u_{0ij} + v_{0j} + \varepsilon_{ijt} \quad (5)$$

where X_{pijt} consists of p time-variant socioeconomic variables at the county level (*LandRentRatio*, *UrbWage*, and *AgriInvest*), X_{qij} includes q time-invariant biophysical variables at the county level (*DistPCapit*, *PlainRatio*, *Elevation*, *Precipitation*, and *Temperature*), which primarily serve as controls for the potential spatial heterogeneities existing across different counties, and Z_{rjt} contains r time-variant socioeconomic variables at the provincial level (*GDP_p*, *UrbWage_p*,

Table 3
Multilevel models for the conversion of cultivated land to urban land.

	Dependent variable: *Log*(*ConvertedLand*)			
	Model 1	Model 2	Model 3	Model 4
Fixed effects				
Within county and between counties				
Intercept	5.909 (0.147)*	6.216 (0.146)*	8.478 (1.369)*	−25.977 (16.490)
Year	−0.458 (0.033)*	−0.500 (0.034)*	−0.502 (0.034)*	−0.670 (0.059)*
$Year^2$	0.045 (0.003)*	0.046 (0.003)*	0.046 (0.003)*	0.055 (0.004)*
LandRentRatio		−0.921 (0.290)*	−0.764 (0.269)*	−0.705 (0.273)*
Log(*UrbWage*)		0.286 (0.086)*	0.348 (0.079)*	0.308 (0.082)*
Log(*AgriInvest*)		0.072 (0.029)*	0.064 (0.025)*	0.063 (0.024)*
Log(*DistPCapit*)			−0.323 (0.041)*	−0.321 (0.042)*
PlainRatio			0.871 (0.206)*	0.858 (0.205)*
Log(*Elevation*)			0.029 (0.026)	0.059 (0.025)*
Log(*Precipitation*)			−0.259 (0.223)	−0.392 (0.222)
Log(*Temperature*)			0.961 (0.293)*	0.856 (0.272)*
Province level				
Log(*GDP_p*)				4.727 (2.033)*
$(Log(GDP\_p))^2$				−0.151 (0.061)*
Log(*UrbWage_p*)				0.486 (0.242)*
Log(*FDI_p*)				0.238 (0.063)*
Random effects				
Within county				
σ_ε^2	1.255 (1.120)	1.267 (1.126)	1.264 (1.124)	1.256 (1.121)
ρ_ε	0.580	0.658	0.761	0.805
Between counties				
σ_u^2	0.639 (0.800)*	0.486 (0.697)*	0.228 (0.478)*	0.236 (0.486)*
ρ_u	0.296	0.252	0.137	0.151
Province level				
σ_v^2	0.268 (0.518)*	0.175 (0.418)*	0.170 (0.412)*	0.069 (0.263)*
ρ_v	0.124	0.090	0.102	0.044

* $p < 0.05$.

and *FDI_p*). The author also included the size of the county as an explanatory variable, found it to be insignificant and therefore omitted it from the model.

In addition to identifying the socioeconomic factors that correlate with urban expansion and cultivated land loss, we are particularly interested in understanding causality and relationships among the factors. The true relationships cannot be identified statistically, but we can examine the relations beyond simple correlations using Granger causality test. The Granger causality test can be applied to time-series data to examine whether lagged values of *X* provide statistically significant information about future values of *Y*, or whether *X* Granger-causes *Y* (Granger, 1969; Granger & Huang, 1997). We conduct separate Granger causality tests to investigate the relationships between our dependent variable *ConvertedLand* and each of the three county-level socioeconomic variables, *LandRentRatio*, *UrbWage*, and *AgriInvest*. Each round of test follows the same procedure. For simplicity, here we denote *Y* for *ConvertedLand* and *X* for *LandRentRatio*, *UrbWage*, or *AgriInvest*. Because the data panel contains only three periods, we can only include one lag in the Granger causality test. First, we estimate a restricted multi-level model for *Y* as a function of its lagged values.

$$Y_{ijt} = \beta_0 + \beta_1 Y_{ijt-1} + \alpha Z_{t-1} + u_{0ij} + v_{0j} + \varepsilon_{ijt} \tag{6}$$

In Eq. (6), *Z* includes all the variables used in estimating Eq. (5) except *X* and *Y*. All indices are the same as previous notations. u_{0ij}, v_{0j}, and ε_{ijt} are the three random terms defined earlier. β_0, β_1, and α are parameters to be estimated. Next, we estimate an unrestricted multi-level model for *Y* as a function of its lagged values and the lagged values of *X*.

$$Y_{ijt} = \beta_0 + \beta_1 Y_{ijt-1} + \beta_3 X_{ijt-1} + \alpha Z_{t-1} + u_{0ij} + v_{0j} + \varepsilon_{ijt} \tag{7}$$

Finally, we use an *F*-test to test the null hypothesis: $\beta_3 = 0$. If $\beta_3 = 0$ is not rejected, lagged *X* values provide statistically significant information about future values of *Y* beyond information contained by lagged values of *Y* and *Z*; otherwise, rejecting the null hypothesis $\beta_3 = 0$ means that lagged *X* values provide statistically significant information about future values of *Y* beyond information contained by lagged values of *Y* and *Z*. In this case, *X* is said to Granger-cause *Y*.

The reverse relationship from *Y* to *X* is tested in the similar fashion. A restricted multi-level model (Eq. (8)) and an unrestricted multi-level model (Eq. (9)) are estimated, followed by a *F*-test with the purpose of examining the null hypothesis of $\beta_3 = 0$. Rejecting the null hypothesis indicates that *Y* Granger-causes *X*.

$$X_{ijt} = \beta_0 + \beta_1 X_{ijt-1} + \alpha Z_{t-1} + u_{0ij} + v_{0j} + \varepsilon_{ijt} \tag{8}$$

$$X_{ijt} = \beta_0 + \beta_1 X_{ijt-1} + \beta_3 Y_{ijt-1} + \alpha Z_{t-1} + u_{0ij} + v_{0j} + \varepsilon_{ijt} \tag{9}$$

5. Results and discussion

We use the three-level nested random intercept model specified in Eq. (5) to estimate models of the conversion of agricultural land to urban areas for 246 urban hotspot counties across 25 provinces. Table 3 displays the estimation results of four multi-level models, with different sets of explanatory variables incorporated. It is expected that a proportion of the variance associated with the base model will be captured by the added predictors, as more information is incorporated for estimating the multi-level model.

In all of the four models, the random effects at both county level and province level are significant. As expected, the variances of the two higher level random terms, namely the variance of between-county intercepts σ_u^2 and the variance of between-province intercepts σ_v^2, generally decrease from Model1 to Model 4 (except σ_u^2 in Model 3). Most of the decline in variances of the two random effects can be attributed to the amount of variability that is accounted for by sequentially including additional predictors. The intraclass correlation coefficients ρ_ε, ρ_u, and ρ_v in Model 1 suggest that 58% of the total variance is attributable to the variation within counties, 30% to the variation between counties in the same province and 12% to the variation between provinces. This shows a considerable degree of clustering in terms of the outcome of agricultural-urban land conversion at all three levels. Despite the differences in the value of the intraclass correlation coefficients between the four models, there is evidence of clustering at the two higher administrative levels. We therefore conclude that two random intercepts are required to adequately represent the nested nature of the underlying processes.

There are three groups of fixed effects estimated from the multilevel models: a set of socioeconomic variables at the county level, a set of time-invariant biophysical factors at the county level, and a set of socioeconomic variables at the province level. In all four models, the time trends show up in a nonlinear fashion, as shown by the statistically significant negative coefficient estimate of *Year* and the significant positive coefficient estimate of $Year^2$. This suggests that over time, the urban expansion placed increasingly less pressure on cultivated land conversion in urban hotspot counties. This is expected. After the mid-1990s, the national government enacted various land regulations which many scholars claim to have slowed down the rate of cultivated land conversion (Liu et al., 2005; Tan, Li, & Lu, 2005). For example, in 1998, the central government revised the Land Management Ordinance, intended to strengthen farmland protection (Lin & Ho, 2005).

Each of the socioeconomic variables at the county level contributes significantly to the amount of conversion of cultivated land to urban uses. The signs on these coefficients are consistent and the differences in their magnitudes are minor, even when more predictors are added into the model. We then use the full model (Model 4), the most comprehensive one, to illustrate the effect of each variable within the group. *LandRentRatio*, a proxy of the ratio of agricultural land rent relative to urban land rent in a county, is negatively correlated with the urban conversion of cultivated land. This indicates that it may be less desirable to convert land to urban uses if the returns to agricultural uses are high. This result conforms to the prediction of the bid-rent model. However, we need to be cautious for this interpretation given that the land leasing market in China is highly immature and the proxy that we use can only roughly capture the information about land rents. The coefficient estimate associated with Log(*UrbWage*) has a positive coefficient. Since this coefficient represents elasticity, the value estimated in Model 4 indicates that as urban wages rise by 10%, the area of cultivated land converted into urban land increases by 3.08%. This is reasonable because when wages increase in non-agricultural sectors, the opportunity costs of farming increase, which can lead to farmland abandonment and a higher risk of the conversion of farmland into non-agricultural uses. Contrary to our expectations, the effect of Log(*AgriInvest*) on cultivated land conversion is positive. The goal of agricultural investments is to increase agricultural productivity and to keep farmland in agricultural production. However, our results suggest that there is a policy failure: agricultural investments lead to cultivated land conversion in urban hotspot counties. There are two explanations for this. First, agricultural investments essentially subsidize agricultural production. These investments do target the most productive cultivated lands; they are available to all farmers. Therefore, some farmland that is less productive than others may be converted to urban uses while the most productive farmland—now even more profitable with the agricultural investments—remains in production. Another reason why agricultural investments lead to cultivated land conversion is that the profits from the increase in agricultural productivity are still lower than the profits that could be earned from leasing or selling the cultivated land for commercial, industrial, or residential uses. The policy failure identified by our model conforms to the empirical evidence shown by most case studies in eastern China, while the case studies in middle China are on the opposite: the increase in agricultural input leads to farmland expansion.

Table 4
Causal relationships identified by Granger causality test.

LandRentRatio	→	*ConvertedLand*
ConvertedLand	→	*LandRentRatio*
UrbWage	→	*ConvertedLand*
AgriInvest	→	*ConvertedLand*

We include a group of biophysical variables at the county level in Model 3 and Model 4. These variables do not change over time and are used as controls for cross-county heterogeneities due to geographic and climatic factors. Three variables in this group have significant coefficients in both models and the signs are stable. Log(*DistPCapit*) is negatively correlated with cultivated land conversion, indicating that counties closer to the provincial capital, the administrative, economic and transportation center of a province, are more prone to cultivated land loss as a result of urban expansion. Proximity to the provincial capital is associated with many locational advantages: good transportation and infrastructure, better market access, and better labor market, all of which matter for urban development. *PlainRatio* and Log(*Temperature*) are positively related to the amount of cultivated land conversion. We expect that counties with flatter terrain and warmer climates will experience more urban conversion of cultivated land. Most of China's cultivated land concentrates in the South, which is both relatively warmer and flatter than the rest of the country. These plains and deltaic regions are highly suitable for agriculture but also among the first places to urbanize due to the concentration of people and economies. Moreover, generally areas with good terrain and climate conditions are more attractive to overseas investors, who consider environmental amenities when determining where to allocate their investments (Zheng, Kahn, & Liu, 2010). Log(*Elevation*) is positively correlated with cultivated land conversion in both models but the correlation is only significant in Model 4. Log(*Precipitation*) demonstrates negative correlations with the dependent variable in both models but none of them are significant.

Other than the previously mentioned explanatory variables, a group of socioeconomic variables at the province level is added to Model 4. They provide contextual information about regional economic conditions, and hence facilitate our understanding about how regional factors affect urban expansion and cultivated land loss at the local level in urban hotspot counties. This entire group of factors is significantly correlated with the urban conversion of cultivated land. Log(*GDP_p*) has a nonlinear effect on cultivated land loss, with a negative coefficient for the squared term but a positive coefficient for the root term. This means that counties in provinces with a higher GDP tend to experience more cultivated land loss due to urbanization but the rate of conversion declines as GDP increases. The peak rate of the impact of provincial GDP on land conversion occurs at GDP = 65.7 (billion yuan). Since GDP is also a measure of income, the result indicates that compared to less developed regions, more developed regions are more likely to urbanize. Similar to the effect of local urban wages, average urban wages at the provincial level have a positive effect on cultivated land loss, as shown by the positive coefficient estimate of Log(*UrbWage_p*). This suggests that the effect of higher urban wages and resulting higher opportunity costs of farming exists both at the local and the regional levels. With the declining importance of urban residency status, the rise in labor mobility enables agricultural labors to pursue non-agricultural activities, which is also an important factor for farmland abandonment. As expected, Log(*FDI_p*) has a positive impact on local cultivated land conversion. Specifically, a 10% increase in the foreign direct investment for a province is associated with a 2.38% increase in the amount of cultivated land converted in a county within the province. This is consistent with

Table 5
Decomposition analysis of the county-level determinants of land conversion, 1989–2000.

Variables	(a) Estimated parameter	(b) Percentage changes in variables (%)	(c) Impact on converted land area (%)	(d) Contribution (%)
LandRentRatio	−0.705	−0.11	0.078	0.137
UrbWage	0.308	1.17	0.360	0.632
AgriInvest	0.063	0.59	0.037	0.065
ConvertedLand		0.57		1

Note: Column a represents the coefficient estimate of each variable based on Model 4. Column b corresponds to the change in percentage of the mean of each variable between 1989 and 2000 (except that change in ratio is calculated for *LandRentRatio*). Multiplying Column a and Column b for each variable arrives at Column c. The contribution of each variable to the change in converted land area in Column d is derived by dividing each element in Column c by the percentage change in *ConvertedLand* (0.57).

the well-documented role of foreign direct investment in funding the construction of large infrastructure and real estate projects (Broadman & Sun, 1997).

One caveat that bears noting is the potential that spatial autocorrelation is biasing the estimates of the standard errors and coefficients. To explore this, we calculated Moran's I statistic for each period of the data and obtained values of 0.33, 0.24 and 0.36, indicating significant spatial correlation for all three periods. Next, we examined how the spatial autocorrelation will affect the estimation results of our model by including the spatial lag of the dependent variable (Weight × log of converted land) as an extra explanatory variable, re-estimating the model, and comparing the results from the new and original models. This comparison illustrates that our original estimation results are robust. For example, for Table 3, all the coefficient estimates maintain their signs and only one of them becomes insignificant. The comparison between the original and new models provides some assurance that the problem of spatial dependence does not jeopardize our estimation results. Nevertheless, this is an issue that may warrant additional exploration in future research.

The results of the Granger causality test provide evidence about the causal relationships between each of the county-level socioeconomic predictors and the response (Table 4). Based on the 95% significance level for the F-test ($p < 0.05$), all of the three tested predictors—the land rent ratio between agriculture and urban areas, urban wages, and agricultural investments per capita—Granger cause the conversion of cultivated land to urban areas. The area of converted land appears to Granger cause the land rent ratio, but not the other two predictors. The test results also show that there are certain level of dynamics and interactions between the relative land rent and the urban development and cultivated land conversion. As a consequence, a relative higher urban land rent stimulates more cultivated land conversion, which in turn can result in a further rise of the urban land rent of this area. This is not surprising. No matter what its form, new urban development typically occurs near existing urban areas. This is likely to be peripheral development that is continuous to the urban core or leapfrog and peri-urban development near existing cities. The boosting feedback mechanism between urban land rent and urban development determines that farmland near existing urban areas is the place first at risk for being converted.

We further explore the estimation results in order to derive more information on the ranking of the importance of the county-level socioeconomic variables in determining the urban conversion of cultivated land. Approaches from previous work that studies the determinants of the spatial scale of cities include ranking the importance of factors according to the size of their elasticities (Brueckner & Fansler, 1983; McGrath, 2005) and decomposition analysis (Deng et al., 2008). Elasticities are measurements of the marginal effects and they show the percentage change in Y associated with a percentage change in X. Nevertheless, using elasticities as indicators of the importance of factors can be misleading considering the fact that X may be less relevant to the change in Y if X changes very little over the period when the change in Y is measured, even if the elasticity of Y relative to X is large. Therefore, we implement the decomposition analysis which accounts for both the size of the marginal effects and the size of the change of the predictors to rank the importance of factors. The results of the decomposition analysis (Table 5) based on the estimation results of Model 4 display the relative importance of the three county-level socioeconomic variables on the urban conversion of cultivated land. In spite of the different signs associated with the marginal effects of the three predictors, their total effects, which incorporate the changes in the predictors, are all positive. The urban wages is the most important factor and it explains 63.2% of the cultivated land conversion due to urban expansion. Without the involvement of other factors, the converted land area would have increased by 36% with the 117% increase of urban wages. The land rent ratio exerts less but still substantial influence, accounting for 13.7% of the cultivated land conversion, while the total impact of agricultural investments is quite small. As a consequence, urban wages and land rent ratio, jointly explaining 77% of the urban land expansion, have been identified as two most influential factors.

6. Conclusion

In this paper, we used multi-level modeling techniques to examine the socioeconomic and policy factors across multiple scales that drive the urban conversion of cultivated land in urban hotspot counties. Our results show that at the county level, both urban land rent and urban wages are essential factors that cause the conversion of cultivated land. Contrary to expectations, agricultural investment drives farmland conversion, suggesting a policy failure associated with its performance. At the provincial level, urban wages and foreign direct investments both positively contribute to urban development and cultivated land loss. We also find that higher GDP is correlated with more urban land expansion but that the relationship is nonlinear. Finally, the Granger causality test identifies an interrelationship between the land rent ratio of agriculture and urban uses and cultivated land conversion. The decomposition analysis illustrates that overall urban wages and land rent ratio are most important in explaining the cultivated land conversion due to urban expansion.

China's urban planning and urban development have become increasingly decentralized and unstructured. The multi-level model allows us to take account of this new trend of urbanization and test differences in urban planning policies and urban land prices across regions. Moreover, our results reveal the relative importance of local versus regional socioeconomic factors on urban expansion. Overall local factors (land rents, urban wages, and agricultural investments) play a dominant role in determining urban expansion. They can be viewed as proximate drivers that are immediately responsible for the observed urban land-use change. Regional factors (GDP, urban wages, and foreign direct investments) also significantly affect urban expansion, although the trajectories by which they exert the influence are not completely clear. Further, local land users have less control power over those higher-level factors that are generally exogenous to the micro-environment of local land users. Our study also sheds some light on the control of future urban expansion and cultivated land loss in urban hotspot counties. The negative effect of relative land rent ratio indicates that it will be less desirable to convert land to urban uses if the returns to agricultural uses are high. In this case, an agricultural subsidy, with the purpose of raising the returns to cultivated land, may be an option for slowing the land conversion. However, our results also suggest that both the strength of this subsidy and the effective allocation and management of the funds are important for the success of the policy.

Acknowledgements

This research was supported by NASA grant NNX11AE88G. The land use data was supported by the National Key Programme for Developing Basic Science of China (2010CB950904) and the National Scientific Foundation of China (41171434). The authors would like to thank Qingling Zhang and Peter Christensen for help with and discussions on the hotspot analysis, and thank the reviewers for their comments and helpful suggestions on the paper.

References

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis*, *27*(2), 93–115.

Anselin, L., Syabri, I., & Kho, Y. (2006). GeoDa: An introduction to spatial data analysis. *Geographical Analysis*, *38*(1), 5–22.

Barlowe, R. (1978). *Land resource economics*. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Beckmann, M. J. (1969). On the distribution of urban rent and residential density. *Journal of Economic Theory*, *1*(1), 60–67.

Bliese, P. (2002). *Multi-level modeling in R: A brief introduction to R, the multi-level package, and the NLME package*. Silver Spring, MD, USA: Walter Reed Army Institute of Research.

Bockstael, N. E. (1996). Modeling economics and ecology: The importance of a spatial perspective. *American Journal of Agricultural Economics*, *78*(5), 1168.

Broadman, H. G., & Sun, X. (1997). The distribution of foreign direct investment in China. *The World Economy*, *20*(3), 339–361.

Brueckner, J. K., & Fansler, D. A. (1983). The economics of urban sprawl: Theory and evidence on the spatial sizes of cities. *The Review of Economics and Statistics*, *65*(3), 479–482.

Chen, J. (2007). Rapid urbanization in China: A real challenge to soil protection and food security. *Catena*, *69*(1), 1–15.

Cheng, J., & Masser, I. (2003). Urban growth pattern modeling: A case study of Wuhan city, PR China. *Landscape and Urban Planning*, *62*(4), 199–217.

Chow, G. C. (1994). *Understanding China's economy*. Singapore: World Scientific Pub Co Inc.

Chuang-lin, F. (2009). The urbanization and urban development in China after the reform and opening-up. *Economic Geography*, *29*(1), pp. 19–25 (in Chinese).

Conelly, W. T. (1994). Population pressure, labor availability, and agricultural disintensification: The decline of farming on Rusinga Island, Kenya. *Human Ecology*, *22*(2), 145–170.

Deng, X., Huang, J., Rozelle, S., & Uchida, E. (2008). Growth, population and industrialization, and urban land expansion of China. *Journal of Urban Economics*, *63*(1), 96–115.

Deng, X., Huang, J., Rozelle, S., & Uchida, E. (2010). Economic growth and the expansion of urban land in China. *Urban Studies*, *47*(4), 813–843.

Deng, X., Liu, J., Zhan, J., & Zhao, T. (2002). Modeling the relationship of land use change and some geophysical indicators: A case study in the ecotone between agriculture and pasturing in Northern China. *Journal of Geographical Sciences*, *12*(4), 397–404.

Doll, C. N. H., Muller, J. P., & Morley, J. G. (2006). Mapping regional economic activity from night-time light satellite imagery. *Ecological Economics*, *57*(1), 75–92.

Eng, I. (1997). The rise of manufacturing towns: Externally driven industrialization and urban development in the Pearl River Delta of China. *International Journal of Urban and Regional Research*, *21*(4), 554–568.

Gelman, A., & Hill, J. (2007). *Data analysis using regression and multi-level/hierarchical models*. New York, NY, USA: Cambridge University Press.

Geoghegan, J., & Pritchard, L. (1998). 'Socializing the pixel' and 'pixelizing the social' in land-use and land-cover change. *People and Pixels: Linking Remote Sensing and Social Science*, 51–69.

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, *37*(3), 424–438.

Granger, C. W. J., & Huang, L. L. (1997). *Evaluation of panel data models: Some suggestions from time series*. University of California, San Diego, Dept. of Economics.

He, C., Okada, N., Zhang, Q., Shi, P., & Li, J. (2008). Modelling dynamic urban expansion processes incorporating a potential model with cellular automata. *Landscape and Urban Planning*, *86*(1), 79–91.

Hoshino, S. (2001). Multi-level modeling on farmland distribution in Japan. *Land Use Policy*, *18*(1), 75–90.

Houkai, W. (2002). Effects of foreign direct investment on regional economic growth in China. *Economic Research Journal*, *4*, 19–26.

Lichtenberg, E., & Ding, C. (2008). Assessing farmland protection policy in China. *Land Use Policy*, *25*(1), 59–68.

Lin, G. C. S., & Ho, S. P. S. (2005). The state, land system, and land development processes in contemporary China. *Annals of the Association of American Geographers*, *95*(2), 411–436.

Liu, J., Liu, M., Deng, X., & Zhuang, D. (2002). The land use and land cover change database and its relative studies in China. *Journal of Geographical Sciences*, *12*, 275–282.

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

Liu, J., Zhan, J., & Deng, X. (2005). Spatio-temporal patterns and driving forces of urban land expansion in China during the economic reform era. *Ambio*, *34*(6), 450–455.

Long, H., Tang, G., Li, X., & Heilig, G. K. (2007). Socio-economic driving forces of land-use change in Kunshan, the Yangtze River Delta economic area of China. *Journal of Environmental Management*, *83*(3), 351–364.

McGrath, D. T. (2005). More evidence on the spatial scale of cities. *Journal of Urban Economics*, *58*(1), 1–10.

Moses, L., & Williamson, H. F., Jr. (1967). The location of economic activity in cities. *The American Economic Review*, *57*(2), 211–222.

Osgood, D. W., & Smith, G. L. (1995). Applying hierarchical linear modeling to extended longitudinal evaluations. *Evaluation Review*, *19*(1), 3.

Overmars, K. P., & Verburg, P. H. (2006). Multi-level modelling of land use from field to village level in the Philippines. *Agricultural Systems*, *89*(2–3), 435–456.

Pan, W. K. Y., & Bilsborrow, R. E. (2005). The use of a multi-level statistical model to analyze factors influencing land use: A study of the Ecuadorian Amazon. *Global and Planetary Change*, *47*(2–4), 232–252.

Pannell, C. W. (2002). China's continuing urban transition. *Environment and Planning A*, *34*(9), 1571–1590.

Pingali, P. (2007). Westernization of Asian diets and the transformation of food systems: Implications for research and policy. *Food Policy*, *32*(3), 281–298.

Polsky, C., & Easterling, W. E. (2001). Adaptation to climate variability and change in the US Great Plains: A multi-scale analysis of Ricardian climate sensitivities. *Agriculture, Ecosystems & Environment*, *85*(1–3), 133–144.

Rosenthal, S. S., & Helsley, R. W. (1994). Redevelopment and the urban land price gradient. *Journal of Urban Economics*, *35*(2), 182–200.

Schneider, A., Seto, K. C., & Webster, D. R. (2005). Urban growth in Chengdu, Western China: Application of remote sensing to assess planning and policy outcomes. *Environment and Planning B: Planning and Design*, *32*, 323–345.

Seto, K. C., & Kaufmann, R. K. (2003). Modeling the drivers of urban land use change in the Pearl River Delta, China: Integrating remote sensing with socioeconomic data. *Land Economics*, *79*(1), 106–121.

Seto, K. C., Kaufmann, R. K., & Woodcock, C. E. (2000). Landsat reveals China's farmland reserves, but they're vanishing fast. *Nature*, *406*(13), 121.

Shen, J., Wong, K., & Feng, Z. (2002). State-sponsored and spontaneous urbanization in the Pearl River Delta of south China, 1980–1998. *Urban Geography*, *23*(7), 674–694.

Snijders, T. A. B., & Bosker, R. J. (1999). *Multi-level analysis: An introduction to basic and advanced multi-level modeling*. London, UK: SAGE Publications Ltd.

Sutton, P. C., & Costanza, R. (2002). Global estimates of market and non-market values derived from nighttime satellite imagery, land cover, and ecosystem service valuation. *Ecological Economics*, *41*(3), 509–527.

Tan, M., Li, X., & Lu, C. (2005). Urban land expansion and arable land loss of the major cities in China in the 1990s. *Science in China Series D: Earth Sciences*, *48*(9), 1492–1500.

Tan, M., Li, X., Xie, H., & Lu, C. (2005). Urban land expansion and arable land loss in China – A case study of Beijing-Tianjin-Hebei region. *Land Use Policy*, *22*(3), 187–196.

United Nations. (2009). *The 2009 Revision of World Urbanization Prospects*.

Vance, C., & Iovanna, R. (2006). Analyzing spatial hierarchies in remotely sensed data: Insights from a multi-level model of tropical deforestation. *Land Use Policy*, *23*(3), 226–236.

Verburg, P. H., Schot, P. P., Dijst, M. J., & Veldkamp, A. (2004). Land use change modelling: Current practice and research priorities. *GeoJournal*, *61*(4), 309–324.

Von Thunen, J. (1826). *The isolated state English edition*. London: Pergamon.

Wang, Y., & Scott, S. (2008). Illegal farmland conversion in China's urban periphery: Local regime and national transitions. *Urban Geography*, *29*(4), 327–347.

White, M. J. (1988). Location choice and commuting behavior in cities with decentralized employment. *Journal of Urban Economics*, *24*(2), 129–152.

Xie, Y., Fang, C., Lin, G., Gong, H., & Qiao, B. (2007). Tempo-spatial patterns of land use changes and urban development in globalizing China: A study of Beijing. *Sensors*, *7*(11), 2881–2906.

Zhang, Q., & Seto, K. C. (2011). Mapping urbanization dynamics at regional and global scales using multi-temporal DMSP/OLS nighttime light data. *Remote Sensing of Environment*, *115*(9), 2320–2329.

Zheng, S., Kahn, M. E., & Liu, H. (2010). Towards a system of open cities in China: Home prices, FDI flows and air quality in 35 major cities. *Regional Science and Urban Economics*, *40*(1), 1–10.