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Do Trees Grow with the Economy? A Spatial Analysis of the Determinants of Forest Cover Change in Sichuan, China

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Abstract This paper aims to identify the relationship between economic growth and forest cover change in Sichuan, China. Using a set of panel land use data based on Landsat TM/ETM digital images, we show that during the late 1980s and 1990s, Sichuan's forest cover initially decreased and then rose. We also note that the rising and falling trends occurred at the same time that Sichuan's economy was going through a period of rapid and sustained growth. We use multivariate analysis to identify the determinants of forest cover change. In addition to using a first-differenced estimator, we also utilize spatial error and spatial lag models to obtain consistent and efficient estimates of the determinants of forest cover. Our analysis demonstrates the importance of economic growth on the forest cover change; the results show that there is a U-shaped relationship between forest cover and GDP per capita. However, despite the nature of the empirical relationship between forest cover and income, the high turning point of the U-shaped relationship suggests that there is no evidence for the existence of the Environmental Kuznets Curve for forests in Sichuan Province. Hence, policy interventions may be necessary to stop the decrease of forests.

Keywords China · Economic growth · Environmental Kuznets Curve · Forest resources · Remote sensing · Spatial econometrics

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1 Introduction

The world's forests provide important ecosystem services including carbon sequestration, reduction of soil erosion and biodiversity. With economic growth, however, these ecosystem services have been measured and shown to diminish over time due to declining forest resources. From 1990 to 2005 the world lost 3% of its total forested area, an average decrease of approximately 0.2% per year (FAO 2007).

Like other parts of the world, China has experienced rapid economic growth during the past few decades; its forest resources also have undergone substantial changes. According to scientists and resource economists, deforestation has been the primary cause of resource degradation in China's Yellow River and Yangtze River Basins (World Wildlife Fund 2003). Excessive commercial logging and clearing of the forest for use as cultivated land in the upper and middle reaches of the basins led to severe consequences in downstream areas. The literature documents the fact that increased soil erosion has silted streams, reduced hydraulic capacity of many river basins and caused higher flood frequencies (Smil 1993; Huang et al. 1999; World Wildlife Fund 2003).

Perhaps surprisingly, in recent years the nature of the changes in China's forestry sector has shifted, a change that may be related to the performance of the economy. Unlike the rest of the world as a whole, China's forests have begun to grow. Between 2000 and 2005 China's forests grew on average by 2.2% annually (FAO 2007). Why has China been able to experience a net increase in forest resources? One possible reason may have to do with the high rate of economic growth in the country. During the same period that China's forests have begun to expand, the rate of increase of the nation's GDP rose by around 10% annually (ZGTJNJ 2006).

While there is a correlation between forest growth and economic expansion in China, there are many other factors that could be driving the shifts in forest resources. It is unclear, ex ante, if economic growth should be expected to contribute to the rise in forest resources. More specifically, in thinking about whether or not economic growth should be expected to encourage forest expansion or lead to more rapid deforestation, there are both positive and negative forces. On the one hand, the net increase in forest growth may be a culmination of a series of massive reforestation and afforestation efforts, which are enabled by rising fiscal resources in the hands of the government. Programs such as the Sloped Land Conversion Program require large investments of fiscal resources that can only be generated when there is fast growth. Other programs, such as the Natural Forest Protection Program, also require large investments and also necessitate the use of large foreign exchange reserves to import forest products that no longer are available from domestic sources (Wang et al. 2007a).

On the other hand, forest resources may be subject to rising pressures as the economy grows. For example, there may be a tendency to exploit timber resources when there is an increasing market demand for goods and services that contain wood components (Foster and Rosenzweig 2003). As a result, without empirical evidence it is unclear if economic growth will raise the demand for the services that forests provide and lead to deforestation, or if rising wealth will provide policymakers with other options for accessing forest and agricultural commodities and allow them to take measures to conserve and expand forest area.

It is equally plausible that rising economic growth pushes rural households deeper into forests as well as allowing them to shift their productive activities from rural areas into urban areas. In one case, there would be a decline in the stock of forest resources. In the other case, there would be a reduced dependency on forest resources for livelihoods and a rise in forest resources. If we knew whether China's forest resources are rising or falling with economic growth, we would be able to better provide policy advice to China's leaders who are in the process of deciding the degree to which the government needs to intervene in the forest sector as the nation goes through its period of rapid economic growth.

Another way of motivating the puzzle that we are interested in can be done by reference to the Environmental Kuznets Curve (EKC). The EKC is a hypothesized inverted U-shaped relationship between environmental degradation and economic growth level, or a U-shaped relationship between the quality of some natural resource and economic growth level (Xepapadeas 2005). The idea behind the EKC suggests that in the early stages of economic growth, environmental quality including natural resource stock may deteriorate with the economic growth (usually represented by GDP per capita). However, beyond a certain level of income, the environment may improve as a result of additional economic growth. In many applications, the indicator of environmental quality is modeled as a quadratic function of income (Stern 2004). This paper investigates whether the forces that underlie the EKC are in effect for the case of forests in China.

The overall goal of this paper is to investigate the relationship between economic growth and changes in forest cover in Sichuan Province, one of the most important regions in China's forest sector (Sayer and Sun 2003). To achieve this overall goal, we have three specific objectives. We first investigate to what extent has the forest cover in Sichuan province changed between 1988 and 2000. Next, we seek to identify the factors that are driving the changes in China's forests. We examine both socioeconomic factors and geophysical factors. Lastly, holding these factors constant, we then investigate whether an EKC for forests exists in China. If there is any evidence for an EKC, we then seek to measure exactly where on the EKC (that is, at which stage of the EKC) is Sichuan.

To meet these objectives, we use a series of approaches from the economics literature. In order to track the changes over time and across space, we utilize satellite remote sensing data that will allow us to chart shifts in land use, including changes in the nature of Sichuan's forest. Remote sensing data will be supplemented by other geophysical and climatic variables as well as a set of social economic variables, including GDP per capita. Based on these data, we use descriptive statistics and GIS spatial analysis to answer how and where the forest cover has changed from 1988 to 2000. Once the trends have been documented, we compare a number of different multivariate approaches (pooled cross-sectional models; first-differenced models; and spatial econometric models) to investigate the determinants of forest cover change. These same sets of approaches will be used to identify the relationship between economic growth and forest cover, our ultimate objective.

Despite this study's advantage in utilizing a set of high quality, spatially detailed data, there are limitations. First, we only study one province. As a result, the results of our study may not be applicable in all of China. In addition, it should also be noted that although Sichuan province's economy is growing fast, it is still one of China's poorest provinces. In 2005, per capita annual gross income in the rural sector of Sichuan was still only 2,782 Yuan (US$ 336).[1]

Despite these limitations, Sichuan is a suitable location to test the EKC for forests. Sichuan contains China's most widespread forest area. It also is considered to be a leader in the setting of forest policy (Sayer and Sun 2003). A number of key forest policies, such as the Natural Forest Protection Program and the Sloped Land Conversion Program, policies that eventually became nationwide efforts, were both initially piloted in Sichuan (Xu et al. 2002). Because of this, we believe there are general lessons that can be learned from a study of Sichuan.

[1] Consumer price index (CPI) in rural area used here is 1.494 (CPI in 2000 = 1.0). Throughout this manuscript, we use the nominal exchange rate in 2000 (US$1 = 8.28 Yuan).

The rest of the paper is organized as follows. In the next section we first review the EKC hypothesis and the previous empirical literature in China and elsewhere. In the following sections we describe our study region and the data. In the next two sections we elaborate on our identification strategy, specify the empirical models that we use for the statistical estimation and present and discuss the results. The final section concludes.

2 Forest Environmental Kuznets Curve

The EKC is a hypothesized non-linear relationship between various indicators of environmental degradation and GDP per capita (Xepapadeas 2005). In the early stage of an economy's growth, environmental conditions, such as air quality, water quality and natural resource stocks, may deteriorate. However, beyond a certain income level the trend may reverse so that beyond that point (the turning point in the EKC) additional economic growth leads to environmental improvement. In sum, this hypothesis suggests that graphs of a number of different environmental indicators trace out an inverted U-shaped shape with income on the horizontal axis and the environment degradation indicator on the vertical axis.

Far from being an academic curiosity, the EKC is of considerable importance to national and international environmental and economic policy-making (Van and Azomahou 2007). The major implication drawn from EKC studies for environmental policy is to determine whether or not (or what type of) policy intervention is necessary. If there is a strong EKC relationship, without any explicit policy intervention, the deterioration of the environment will slow and reverse itself as the economy grows. In other EKC studies, authors have used the results to understand whether or not policy programs that move the economy to a sustainable development path are needed to flatten or eliminate the EKC (Bhattarai and Hamming 2002).

Since the EKC concept emerged in the early 1990s, the EKC hypothesis has been used as the basis of motivation of a number of studies examining the relationship between economic growth and different pollutants, such as sulfur dioxide and particulate matter in the atmosphere (Selden and Song 1994; Grossman and Krueg 1995; Panayotou 1997). Many of these studies have consistently found fairly strong evidence in support of the EKC. More recently, concern about global warming and declining biodiversity has led to interest in seeking to understand the relationship between social-economic factors, including economic growth, and the state of natural resources (Foster and Rosenzweig 2003).

However, unlike the case of flow types of pollution, such as air and water pollution, the findings from empirical studies testing the presence of an EKC relationship between economic growth and the stock of a natural resource are mixed (Bhattarai and Hamming 2002). In the case of forest resources, several studies have found empirical evidence supporting an EKC relationship for the process of deforestation (Cropper and Griffiths 1994; Bhattarai and Hamming 2002; Foster and Rosenzweig 2003). These studies have documented that at low levels of economic growth in Africa, Latin America and Asia, deforestation rises. Beyond a certain level of income, however, the process of deforestation has been found to slow down. In contrast, two studies, Shafik (1994), which used panel data with fixed effects on a sample of 66 countries between 1962 and 1986, and Koop and Tole (1999), which used a sample of 76 tropical developing countries over a period of 1961–1992, did not find an EKC for deforestation. More recently, Van and Azomahou (2007) used parametric and semiparametric models to analyze panel data from a number of different countries over a number of different time periods and also found no evidence of an EKC for deforestation.

In the context of China, studies on the existence of an EKC relationship between economic growth and China's forests also have produced mixed results, perhaps due in part to lack of reliable forest data. For example, Zhang et al. (2006) estimated models of the determinants of forested area in a study of China at the national, regional and provincial levels using panel data for 12 years (1990–2001). With the basic observation measured at the province level, their study found that there was an EKC-type inverted U-shaped relationship between income per capita and the forested area. In fact, the EKC is found in 21 out of 30 provinces, including Sichuan, and, according to the study, the relationship is already approaching the last stage of forest EKC (that is, deforestation is falling as income is rising). In contrast, Wang et al. (2007b) used provincial forest inventory data over the past two decades to show that there was not convincing empirical evidence for a well-behaved forest EKC. While interesting and important, these studies lack spatial detail in inventory data. Changes in both forest resources and economic growth can vary significantly within provinces (i.e., across counties and towns.) Under such circumstances, disaggregated and spatially detailed data likely are more suitable for better understanding the relationship between economic growth and forests. In contrast to the previous literature, we use more spatially detailed data to examine the relationship between forest cover and economic growth.

3 Study Area and Data

The study site of our research, Sichuan province in southwest China, is arguably a good location to study the relationship between economic growth and forest cover. Sichuan province covers a vast area of 485 thousand square km (5% of China's total area) and is one of the most populated provinces in China (86.0 million according to the 2000 census). Sichuan also hosts one of the strongest economies in Western China. Since 1995, Sichuan's gross domestic product (GDP) has grown steadily. Between 1995 and 2000, real GDP per capita in Sichuan increased from 3,283 Yuan (US$ 396) to 4,805 Yuan (US$ 580, ZGTJNJ, 1996 and 2001).[2] The real GDP per capita of Sichuan province in 2008 reached 8,767 Yuan (US$ 1,059, Statistical Bureau of Sichuan Province 2006).[3]

During the past several decades, in addition to rapid economic changes, Sichuan also has experienced substantial changes in its forest resources. Although accurate forest statistics over time are hard to come by, several studies indicate that from 1960s to 1980s, the forest cover in Sichuan declined from around 20% to 13%, mainly due to timber harvesting (Smil 1993). The SFA's forest inventory data, however, show that by 2000, the forest cover in Sichuan recovered to nearly 30% (SFA 2004).

While there is a lot of interesting variability over time for Sichuan as a whole, there also is a lot of variability across space within Sichuan in terms of economic growth and changes in forest resources.[4] Because of this heterogeneous nature, more spatially detailed disaggregated

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[2] Consumer price index used for 1995 is 0.9147 (CPI in 2000 = 1.0).

[3] Consumer price index used here is 4.71 (CPI in 1978 = 1.0).

[4] According to county level data, there are great differences among counties in their economic growth rates. Between 1995 and 2000, the GDP of some counties, such as Mianyang and Yanbian, grew by more than 100%. During the same period there was low, no or negative growth in other counties, such as Deyang and Seda (NBSC 2001). Similarly, some regions in Sichuan experienced a decline in forest cover while others experienced a growth in forest cover. For example, Pingwu county and Anxian county experienced severe deforestation between 1995 and 2000. In other areas, such as Zigong and Tianquan counties, forest cover increased significantly.

forest data are clearly called for when studying the relationship between economic growth and forest resources.

The need to understand the impact of Sichuan's rapid economic growth on its forests is underscored by the richness of the province's forest sector. Sichuan province has considerable importance in forest products production in both timber products and non-timber forest products (Rozelle et al. 2003). Gross output value of forestry in Sichuan accounted for more than 5% of the national total value in 2003 (ZGTJNJ 2003). In the 2009 timber harvest plan made by State Forestry Administration, Sichuan's timber harvest will contribute to about 3% of total timber harvest in China (SFA 2008). In terms of *matsutake*, an important non-timber product exported to Japan, Southwest China (mainly southwest Sichuan and northwest Yunnan provinces) accounts for almost 80% of China's total production (Liu 2006).

In part because of its vast forest resources, and in part because of its status as a province with both a vibrant collective and state-owned forest sector, Sichuan has been a leader in national forestry policy. In the case of two of the nation's most important forestry policies over the past decade—the National Forest Protection Plan and the *Grain for Green* Program—Sichuan was chosen as a place for the implementation of the earliest pilot programs (Sayer and Sun 2003). Currently, there are still a number of experiments going on now in Sichuan to assess different approaches to State-owned forest reform (Vajpeyi and Ponomarenko 2001).

In summary, for all of these reasons, we believe that Sichuan is a good place to examine the relationship between economic growth and the forest resources. It is a fast growing province economically. Perhaps more important, it also is a large province with differences across its space in economic growth and forest resources. We hope because of these attributes, a study of Sichuan can serve as an important case study and that it will stimulate future research in other areas.

3.1 Data

One of the strengths of this research is the quality and reliability of the forest data that we use. Unlike the forest inventory data that many previous studies have used (which are aggregated at the provincial level and vary in quality over time), we use satellite remote sensing data. Utilizing US Landsat TM/ETM images with a spatial resolution of 30 m by 30 m, the original dataset was developed by the Chinese Academy of Sciences (CAS). The data set—for all of China and for small sub regions of China—have been used by many other researchers studying Land Use Change (LUC) and the data are regarded by these research teams as high quality (Liu et al. 2002, 2003, 2005; Deng et al. 2007).

In this study, we use the forest data for the years 1995 and 2000. In previous forest EKC literature, some studies have used forest cover or other stock variables (e.g., Foster and Rosenzweig 2003; Zhang et al. 2006; Wang et al. 2007a); other studies have used deforestation rate or other flow variables (e.g, Cropper and Griffiths 1994). With the availability of two years of data, we are able to examine both the forest cover (stock) and the change in forest cover (flow.)

The definition of forest area in our study is a comprehensive one that captures and includes different types of forests. In using the raw LUC data, forest area can be subdivided into four distinct classes: (a) natural or planted forests with canopy cover greater than 30%; (b) land covered by trees less than 2 m high, with a canopy cover greater than 40%; (c) land covered by trees with canopy cover between 10 and 30%; and (d) land used for tea gardens, orchards, nurseries and other forested area. In this paper, we use a single measure of forest area that includes all four types of forest (a + b + c + d). This measure should pick up most of the area in Sichuan that is covered by trees (Deng et al. 2007).

Our GIS database also contains information on several time-invariant geophysical factors and climatic variables, including elevation, slope, average temperature and precipitation. The data for measuring the geographic and climatic factors come most directly from the CAS Data Center, although originally they are from a variety of sources. For example, the data for measuring average rainfall (measured in millimeters per year) and temperature (measured in accumulated degrees centigrade per year) are accessed from the CAS Data Center. However, the data themselves were initially collected and organized by the Meteorological Observation of China, which worked with more than 600 national climatic and meteorological Data Centers over China. For use in our study, we take the point data from the climate stations and interpolate them into surface data using a spline smoothing algorithm. The elevation and terrain slope variables, which measure the nature of the terrain of each 1×1 squared kilometer pixel, are generated from China's digital elevation model data set that are part of the basic CAS data base.

We also use several measures of distance (all of which are measured in kilometers) that are defined separately for each pixel in our sample. Specifically, we produce variables such as the distances to the nearest roads by road type (expressway, highway, provincial way and local road) and the distance to the nearest prefectural cities and/or urban cores. The data for the location of the prefectural cities, the road network and the location of the urban core are from the CAS Data Center.

Two economic and demographic variables, the level of GDP and population, are included in our modeling work. Information on GDP for each county for 1995 and 2000 are from the *Socio-economic Statistical Yearbook for China's Counties* (NBSC 2001). After the early 1990s GDP measures generated by NBSC at all levels of statistical data collection (county, province and national) are consistent. The demographic data for 1995 and 2000 are from the *Population Statistical Yearbooks for China's Counties* which are published by the Ministry of Public Security of China (various years). When there are missing data in the yearbook, the information is supplemented by each province's annual statistical yearbook for 1995 and 2000. In order to get pixel-specific measures of the demographic variables we use an approach called the Surface Modeling of Population Distribution framework to interpolate the data across space (measured as persons/kilometer squared—Yue et al. 2005). The level of GDP (GDP per capita per kilometer squared) is also interpolated across space using commonly available GIS algorithms (Doll et al. 2000, 2006; Deng et al. 2008).

The descriptive statistics produced from our data suggests that there may be an EKC for Sichuan's forests (Table 1). The forest cover in Sichuan decreased from 1988 (30.96%) to 1995 (30.81%) and then increased from 1995 to 2000 (31.02%). During this period, GDP per capita increased by 47% from 1995 to 2000. Based on the GIS data, we find that some areas experienced rapid changes in forest cover while others did not (Fig. 1). Moreover, the relationship between forest cover and GDP per capita may also be correlated with other socio-economic and geophysical factors. In the next section, we explain the identification strategy to isolate the relationship using econometric methods. Unfortunately, since consistent data on economic growth at the county level in China only go back to the early 1990s, we can only perform the multivariate analysis using the data for 1995 and 2000. Descriptive statistics of all variables (sampled data) used in the model are available in the "Appendix" Table 6.

Table 1 Descriptive statistics of key variables

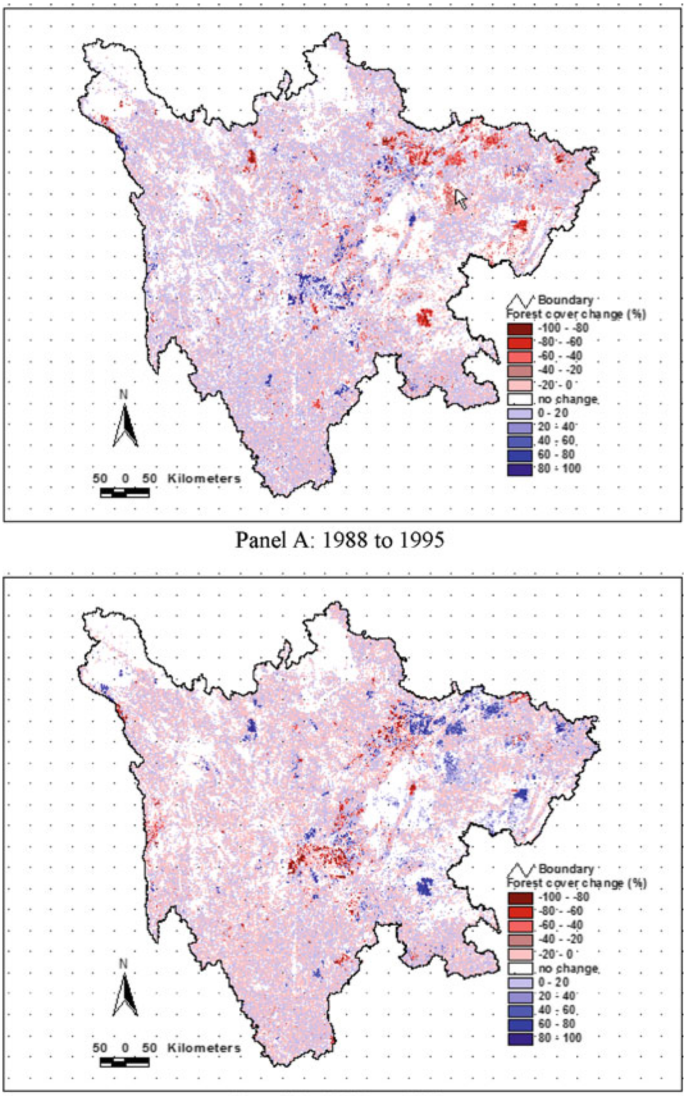
Variable	Mean	Min	Max
Forest cover[a] (%)			
1988	29.36	0	100
1995	28.88	0	100
2000	29.38	0	100
Real GDP per Capita[b] (10,000 yuan)			
1988	NA	NA	NA
1995	0.38	0	754.69
2000	0.50	0	842.63

County-level data for GDP per capita were not available for 1988
[a] *Source*: Authors' data
[b] *Source*: NBSC

3.2 Sampling Strategy and the Monte Carlo Method

The original land use data include information for all of Sichuan. The basic unit of observation (after aggregation from 30×30 m images) is a 1×1 squared kilometer pixel. As indicated above, there are observations from three time periods: 1988, 1995 and 2000.[5] Given Sichuan's size, there are 483,244 pixels in the original dataset. Because the entire dataset is too large to work with conveniently in econometric models, we utilize a sampling strategy which we base on a Monte Carlo approach as a way to derive reliable results (and feasibly use the data).

[5] We develop an approach and a set of programs to generate one kilometer area percentage data to trace the changes of forest areas. The generation of one kilometer area percentage dataset on land uses is based on map-algebra concepts, a data manipulation language designed specifically for geographic cell-based systems. The procedure to generate the one kilometer area percentage data consists of five steps. The first step is to generate land use maps during the study period, in our study, which mean to generate the land use maps of northeast China for 1987, 1995 and 2000 at the scale of 1:100,000. This is done by visual interpretation in the ArcGIS 9.2 software environment. The second step is to generate the one kilometer FISHNET vector map geo-referenced to a China boundary map at the scale of 1:10,000. The third step is to intersect the land-use change map with the one kilometer FISHNET vector map. This is followed by aggregating the conversion areas for each LUT in each one kilometer grid identified by the one kilometer FISHNET vector cell IDs in the TABLE module of Arc/Info 9.2. Finally, the area percentage vector data are transformed into grid raster data to identify the conversion direction and intensification. The design and experienced data handling procedures ensure the zero loss in areas and produce the basic data that are used to trace the changes of forest areas resulting from conversions with various kinds of land uses. For each time period we used more than 20 TM/ETM scenes to cover the entire country. The Landsat TM/ETM images also are georeferenced and orthorectified. To do so, the data team used ground control points that were collected during fieldwork as well as high-resolution digital elevation models. Visual interpretation and digitization of TM images at the scale of 1:100,000 were made to generate thematic maps of land cover. A hierarchical classification system of 25 land-cover classes was applied to the data. In this study the 25 classes of land cover were grouped further into six aggregated classes of land cover—cultivated land, forestry area, grassland, water area, built-up area and unused land. In order to obtain even more accurate estimates of land use, we also designed a matrix that will help us account for the areas in which there are ground objects that are linear in shape. To do so, we use information from aerial patches based on the CAS LUC dataset. The precision of measurement was up to the centimeter level. The width of linear objects, including small canyons, ditches and roads, were measured via the ZOOM IN functions in the ArcGIS 8.02 environment (the smallest of the magnifying function is 10 times). For irregular linear thin objects, we divided them into more regular ones and measured them one by one and then aggregated them into areas of the entire thin objects. When handling the data in this way, we guarantee the accuracy of the discounting of linear thin objects as well as the measurement for the aerial patches. In addition, for small objects, we measured their true areas rather than generalized areas (the traditional way which is less accurate) in order to guarantee the accuracy of aerial patches and ensure that they are relatively free from aggregation errors.



Panel A: 1988 to 1995

Panel B: 1995 to 2000

Fig. 1 Forest cover change in Sichuan: from 1988 to 1995 (**a**) and from 1995 to 2000 (**b**). *Source*: Author's data

To implement our approach, we first draw a sample of 4,832 pixels by choosing one pixel from every 10 × 10 squared kilometer. The sampling is done on a regular pixel basis. In other words, after randomly choosing one pixel in the data set, the rest of the sample was chosen by skipping every nine pixels and choosing the tenth one using a regular sampling strategy.[6] After choosing points in this way, we were left with 1% of the total observations for the first

[6] In ArcGIS grid data set, by setting a reference layer, a feature or raster layer, we use the functions in GRID module of ArcGIS to generate a point layer of regularly spaced points, i.e., every nine points. The first point during the sampling can optionally be placed in the centre of the top-left cell as opposed to the extreme top-left corner.

sample-based dataset. We then repeated the sampling protocol and produced 100 different sampled datasets. By construction, the 100 draws combined covers all the pixels in Sichuan Province (meaning when we sampled for the starting point, we did so without replacement).

After sampling, for each empirical model described in the next section, we ran 100 regressions using those 100 different sampled datasets. Finally, we calculated the averages of the estimates and standard errors using the results from the 100 individual regressions. All of the empirical results reported in this manuscript are from the Monte Carlo analyses.

4 Econometric Analysis

In order to investigate the relationship between economic growth and forest resources, and to test whether there is an EKC for forests in Sichuan, the basic model that we are interested in is:

$$Forest\ Area_{it} = a_0 + a_1 {*} GDP\ Per\ Capita_{it} + a_2 {*} (GDP\ Per\ Capita)^2_{it} + e_{it} \quad (1)$$

where i is an index for each 1×1 squared kilometer pixel; t is an index for year; and a_1 and a_2 are our coefficients of interest.

When estimating the relationship between economic growth and forest resources, it is important to produce unbiased, consistent estimates. To the extent that there are variables that are correlated with the variable of interest and the dependent variable, the estimated coefficient will be biased and the analysis based on the results may be misleading. One way to reduce the potential bias is to control for all available variables that explain forested area in the estimating equation that might be also correlated with economic growth. In addition to a variable that measures economic growth, researchers in previous deforestation studies have found variables such as population (or population density), measures of market access (e.g., distance to roads and distance to the nearest cities), and geophysical features (e.g., temperature, precipitation, slope, elevation) are also key explanatory variables of deforestation (Foster and Rosenzweig 2003; Zhang et al. 2006; Van and Azomahou 2007; Wang et al. 2007a). However, only a few previous forest EKC empirical studies, which explain the effect of economic growth on forest resources, control for the full set of key control variables. Even fewer studies have employed econometric methods to reduce the bias due to omitted unobserved variables (Stern 2004). In response, we extend the basic EKC empirical model in three ways: (a) a pooled cross-sectional model controlling for all available socioeconomic and geophysical variables; (b) a first-differenced model (fixed effects model) which reduces the bias from omitted, time-invariant unobservable variables; and (c) a set of spatial econometric models which attempt to account for the spatial correlation in the data.

In particular, spatial correlation has only recently been considered in the EKC literature. In the first empirical EKC research paper to address spatial autocorrelation in a direct fashion, McPherson and Nieswiadomy (2005) employed spatial lag and spatial log model and found that spatial autocorrelation in present in their data on threatened birds and mammals. Using a panel of emissions data, Maddison (2006, 2007) found that a conventional EKC is augmented by spatially weighted values of the dependent and independent variables. To the best of our knowledge, our study is the first EKC study to take into account of spatial autocorrelation in the context of forest resources.

4.1 Pooled Cross-Sectional Model

To partially reduce the bias resulting from omitted variables that may be correlated with forests, we include both social-economic and geophysical variables in our pooled cross-sectional model to examine the relationship between forest cover and economic growth by controlling for all of the available variables (Hausman and Taylor 1981). In doing so, we estimate the following reduced form model[7]:

$$Forest\ Area_{it} = a_0 + a_1 * GDP\ Per\ Capita_{it} + a_2 * (GDP\ Per\ Capita)^2_{it} + Z_{it}\beta + D_i\gamma + e_{it} \tag{2}$$

where Z_{it} is a NT × K matrix of observations on the time-variant control variables, D_i is a NT × L matrix of observations on the time-invariant control variables, β a K × 1 vector of regression coefficients and γ an L × 1 vector of regression coefficients. The pooled cross-sectional model can be estimated using OLS. The matrix Z_{it} includes the following time-variant following control variables: GDP per capita in the 10 km buffer area, population in the 1 × 1 km pixel, population in the 10 km buffer area, distance to the nearest prefectural city weighted by the GDP of the city, distance to the nearest forest, distance to the nearest urban core, forest area in the 10 km buffer area, cultivated land in the 10 km buffer, and built-up area in the 10 km buffer. To calculate the weighted distance to the nearest prefectural city, we weigh the distance by the GDP of this prefectural city. For example, if the distance between one pixel and the nearest prefectural city from this pixel is equal to the distance between another pixel and its nearest prefectural city, then the weighted distance will be higher for the pixel whose nearest prefectural city has higher GDP.

The matrix D_i includes the following time-invariant variables: distance to the nearest express way, distance to the nearest provincial ways, distance to the nearest county/township roads, distance to the nearest local road, average elevation, average slope, average precipitation and temperature. These time-invariant variables can be used to control for some key, fixed effects of each pixel.[8]

4.2 Results from Pooled Cross-Sectional Model

The coefficient estimates from the pooled cross-sectional model indicates support for the Environmental Kuznets Curve (Table 2). The coefficient for GDP per capita is negative

[7] We also considered estimating the double log model. However, one critical disadvantage of the double log model in our context is that we have more than 100,000 pixels in the study area (before sampling) in which the value of cross-sectional variables (either dependent or explanatory variables or both) have a zero or negative value; these observations would be dropped if we were to use a cross-sectional double log model. Moreover, in a first-differenced model, if the value of the observation of any of the pixels did not change over time, that observation also would suffer from the same problem. Hence, if we were to adopt a double-log framework, we would have insufficient observations to run a model with the same specification as in Table 3. We therefore work primarily with the models with the level variables.

[8] One remaining concern is simultaneity bias that may exist between GDP per capita and forest cover. We tested for the endogeneity of the GDP per capita variable using the Hausman Test for endogeneity (Hausman 1978; Cameron and Trivedi 2005, p. 276). To conduct this test, we need an instrumental variable(s). Following Godoy et al. (2009), the we utilize "ranking of GDP per capita in Sichuan" as an IV for GDP per capita. For each pixel i, we calculate the share of the highest GDP per capita in Sichuan in each year (1995, 2000) as follows:

Share of the highest GDP per capita in Sichuani, 1995 = (GDP per capita in 1995)$_i$/(Maximum GDP per capita in Sichuan in 1995).

We also created the same variable for 2000. Using these variables as the IV, the Hausman test showed that GDP per capita variables in 1995 and 2000 were not endogenous.

Table 2 Monte Carlo estimates of the pooled cross-sectional model

	Dependent variable: *Forest cover*
GDP per capita	−0.745
	(0.270)
(GDP per capita)^2	0.012
	(0.005)
GDP per capita in 10 km buffer area	−0.361
	(1.022)
Population density	−0.008
	(0.001)
Population density in 10 km buffer area in 1995	0.012
	(0.002)
Distance to the nearest prefectural city weighted by GDP	0.000
	(0.000)
Distance to the nearest expressway	−0.029
	(0.017)
Distance to the nearest provincial way	0.021
	(0.017)
Distance to the nearest county/township roads	−0.181
	(0.068)
Distance to the nearest local road	0.683
	(0.109)
Distance to the nearest forest	−3.584
	(0.214)
Distance to the nearest urban core	0.024
	(0.027)
Forest area in 10 km buffer area	0.720
	(0.030)
Cultivated land in 10 km buffer area	0.009
	(0.032)
Built-up area in 10 km buffer area	0.388
	(0.208)
Average elevation	0.000
	(0.001)
Average slope	0.070
	(0.083)
Average precipitation	0.007
	(0.003)
Average temperature	−0.702
	(0.217)
Constant	10.079
	(5.786)
Observations	5,238
R-squared	0.507

Absolute value of standard error in parentheses

and significant, while the coefficient for GDP per capita squared is positive and significant (Table 2). Therefore, based on the results from the pooled cross-sectional model, we observe a statistically significant U-shaped relationship between economic growth and forest cover in Sichuan.

Interestingly, the estimated coefficient of the distance to the nearest forest is negative and the coefficient of the forest area in the 10 km buffer area is positive. Both of the coefficients are statistically significant. Intuitively, this means that there is more forest in one pixel if there is more forest in the areas adjacent to the pixel of interest. One possible explanation may be that the neighboring areas have similar socioeconomic, demographic and geophysical characteristics. Another reason may be that the harvest or planting decision in one pixel may be correlated with the decisions in neighboring pixels (Robalino and Pfaff 2005). Perhaps most significantly, this analysis suggests that the neighborhood effects may be significant and that they need to be considered in any serious analysis.[9]

4.3 First-Differenced Models

Although we have controlled for many socioeconomic and biophysical characteristics, we are still concerned about unobservable factors that affects forest cover and economic growth. If these unobserved factors are highly correlated with both the dependent variable and the independent variable of interest, a model that does not control for these unobserved factors may produce biased coefficients. To control for the unobserved effects that arise from time-invariant unobservables, we use a first-differenced model. The dependent variable in this case is forest cover change. When defining our time variant variables in this way for both the dependent variable and the explanatory variables, all time-invariant variables—both observables and unobservables—will be differenced out. The first-difference equation is expressed by:

$$\begin{aligned}\Delta Forest\ Area_i &= a_1 * \Delta GDP\ Per\ Capita_i \\ &\quad + a_2 * \Delta (GDP\ Per\ Capita^2)_i + \Delta Z_i \beta + \Delta e_i \qquad (3)\end{aligned}$$

where Δ indicates that a variable has been first-differenced. Since our data set is limited to two time periods (1995 and 2000), the first-differenced model is equivalent to a pixel fixed-effects model. In addition, we add a time fixed effect for the year 2000 to capture the time trend.

4.4 Results from the First-Differenced Model

When moving from Table 2 to Table 3, we can see the bias of estimating the determinants of forest area in an estimation framework that does not control for fixed effects. The estimated coefficients of several time-varying variables change significantly. For example, the coefficients of population density and of population in the 10 km buffer area remain negative and positive, respectively, but both of them become insignificant (Table 3).[10]

[9] Turning to other explanatory variables, some of the estimated coefficients of this model are of the expected sign while others are not. Population density is negative and statistically significant determinants of forest area (Table 2). Intuitively, holding GDP per capita and other variables constant, the area with more population may have less forest. This conclusion is consistent with the previous studies (Cropper and Griffiths 1994; Entwisle et al. 2008; Van and Azomahou 2007). However, the estimated positive coefficient on population density in the 10 km buffer area is not consistent with the expectation. The estimated positive coefficients on the distance to the nearest provincial way and the distance to local road are consistent with the intuition that higher travel costs decrease the returns from agricultural land use thus forest become a substitution of cultivated land (Angelsen 2007; Vance and Geoghegan 2002), but the negative coefficients on the distance to the nearest expressway and other roads are not consistent with this intuition. As for the geophysical variables, the estimated coefficients on the average annual precipitation and temperature mean that, the area with more precipitation may have more forest while the area with high temperature may have less forest. The estimated coefficient for elevation is positive but statistically insignificant, slightly different from to the findings of Vance and Geoghegan (2002). The estimated coefficient of slope is statistically not different from zero.

[10] In the estimated first-differenced model, the coefficients of population and of population in the 10 km buffer area remain negative and positive respectively but both of them become insignificant (Table 3, column 2). This indicates that, after controlling for all fixed effects, population has no significant impact on forest cover

Table 3 Monte Carlo estimation of first differenced model

	Dependent variable: *Forest cover change*
ΔGDP per capita	−1.383
	(0.294)
Δ(GDP per capita)^2	0.015
	(0.004)
ΔGDP per capita in 10 km buffer area	1.764
	(1.506)
ΔPopulation density	−0.002
	(0.002)
ΔPopulation density in 10 km buffer area	0.005
	(0.003)
ΔDistance to the nearest prefectural city weighted by GDP	0.0002
	(0.001)
ΔDistance to the nearest forest	−2.521
	(0.361)
ΔDistance to the nearest urban core	−0.018
	(0.057)
ΔForest area in 10 km buffer area	0.696
	(0.045)
ΔCultivated land in 10 km buffer area	−0.182
	(0.063)
ΔBuilt-up area in 10 km buffer area	−0.337
	(0.519)
Time trend (2000)	−1.206
	(0.319)
Observations	2,616
R-squared	0.189

Standard error in parentheses

Most importantly, given the focus of our study, while the signs and levels of significance of some coefficients may have changed when using the first differenced model, the coefficients of GDP per capita variables are still fundamentally the same (in terms of sign and significance). The coefficient on the linear term (*GDP per capita*) is still negative (−1.383) and statistically significant (standard error is 0.294). The coefficient of GDP per capita squared also remains positive and significant. While the magnitude increases from 0.012 to 0.015, in fact, the estimates from the two models are remarkably similar. Hence, the empirical result from this first-differenced model still indicates that there may be a U-shaped relationship between forests and GDP per capita.

Footnote 10 continued
change, with other variables held constant. This result is in stark contrast to the results of other studies which have concluded that population growth leads to deforestation. However the relationship generated by most previous studies remains controversial since there may be forces that simultaneously affect both population and forest cover change, thus making it appear like one is the cause of the other when in fact it may not be (Contreras-Hermosilla 2000). To the extent that our model is correctly identified, we find evidence that population growth is not correlated with forest cover change.

4.5 Spatial Econometric Methods

In addition to the omitted variable bias, we also are concerned about the bias or inefficiency of the estimates due to the spatial correlation in the data. In both of the previous models, the "neighbor effect" was significant, including in the first-differenced model (e.g., the variables for change in distance to the nearest forest and change in forest area in 10 km buffer area). In fact, this type of spatial correlation is what might be expected in a data set composed of such disaggregated pixels across space. If the data contain spatial dependencies, using OLS (model 1) and fixed effects (model 2) techniques can lead to either statistic inconsistent or inefficient estimates which would lead to invalid hypothesis testing procedures (Anselin 1988). In addition to this identification problem, the degree of spatial dependencies is an interest in and of itself when there are neighborhood effects in forest management decisions. Decisions made by one forest manager and his neighboring manager may affect each other simultaneously. For example, one village's decision to maintain the forest for tourism may encourage adjacent neighboring villages also to maintain their forests (Robalino and Pfaff 2005). Any effort that seeks to understand the determinants of forest cover change need to account for this.

To take into account of the possible spatial effects, we employ spatial econometric methods. Spatial econometrics can be used to control for spatial dependencies that can arise from different sources. The two most frequently cited sources of problems arising from spatial dependencies are the spillover effects between the observations of the dependent variable and the spatial correlation between unobservable explanatory variables (i.e., disturbance terms—(Saavedra 2003). For these two sources of spatial dependencies, spatial relationships can be modeled in two ways. One way is to hypothesize that the value of the dependent variable (forest cover change) observed at a particular pixel is partially determined by some function of the values of each of its neighbors. It is typically formulated as a spatially weighted average of the neighboring values, where the neighbors are specified through the use of a so-called spatial weight matrix (Anselin 1988).

Using a general notation, the spatial lag model in matrix form in our study is given by

$$y = \rho\omega y + X\beta + \varepsilon \tag{4}$$

where y is an N×1 vector of the dependent variable, ω denotes the exogenous N×N spatial weight matrix, which specifies the neighbors used in the averaging (resulting in the spatial lag term, ωy), ρ is a scalar spatial autoregressive parameter, X is an N×K matrix of independent variables, β is a K×1 vector of matching parameters, and ε is an n×1 vector of error terms. Positive spatial correlation exists if $\rho > 0$, negative spatial correlation exists if $\rho < 0$ and no spatial correlation exists if $\rho = 0$. The inclusion of spatial lag terms on the right hand side of the equation is motivated by theory as the equilibrium outcome of processes of social and spatial interaction. Applying first-difference Eqs. 3–4 to eliminate fixed effects gives:

$$\begin{aligned}\Delta Forest\ Area_i = {} & \rho\omega\Delta Forest\ Area_i + a_1{*}\Delta GDP\ Per\ Capita_i \\ & + a_2{*}\Delta(GDP\ Per\ Capita)_i^2 + \Delta Z_i\beta + \Delta e_i\end{aligned} \tag{5}$$

Another way of incorporating spatial relationship is by accounting for the spatial dependencies in the error term. When accounting for spatial dependencies embodied in the error term, the model accounts for the situation in which the errors associated with any observation are spatially weighted average of the errors in the neighbor area plus a random error component. Specifically, the spatial error model in matrix form is given by

$$y = X\beta + \varepsilon \quad \text{where } \varepsilon = \lambda\omega\varepsilon + u \tag{6}$$

where ε is a vector of spatially auto-correlated error terms, u is a vector of $i.i.d.$ errors, and λ is a scalar parameter known as the spatial autoregressive coefficient. The errors are positively correlated if $\lambda > 0$, negatively correlated if $\lambda < 0$ and uncorrelated if $\lambda = 0$. Spatial error correlation can result from omitted variables, including spatially weighted independent variables and a spatial lag, and the unobserved spatial heterogeneity in the error structure (Anselin 1988). Applying the first-difference Eqs. 3–6 gives:

$$\begin{aligned} \Delta Forest\ Area_i = {} & a_1 * \Delta GDP\ Per\ Capita_i + a_2 * \Delta(GDP\ Per\ Capita)_i^2 \\ & + \Delta Z_i \beta + \Delta e_i \end{aligned} \tag{7}$$

where $\Delta e_i = \lambda\omega\Delta e_i + \Delta u_i$.

In this analysis, the spatial weight matrix ω was constructed based on the inverse distance between pixels' centroids. The spatial weight matrix defines pixels to be neighbors if the distance between their centroids is less than 800 km. The matrix was then row standardized.

Because of the nature of the correlations in the variance-covariance matrix, Eqs. 5 and 7 cannot be estimated by OLS. The problem is that there is simultaneity bias when OLS is used. Therefore, the model must be estimated by using either an IV estimator or using maximum likelihood techniques. In our study, we use the maximum likelihood techniques to estimate both the spatial error and spatial lag models. We assume that the random errors are normally distributed with a constant variance. To deal with potential heteroskedasticity problem in our data, we report the Huber-White robust standard error. Moreover, to avoid repeating the neighboring effects in one model, two explanatory variables, "forest area in the 10 km buffer area" and "distance to the nearest forest", are deleted from both spatial error and spatial lag models.

4.6 Specification Tests

To incorporate the spatial associations in the dependent variable and in the explanatory variables, we first perform specification tests to specify the structure of the spatial effects in the regression model. Specifically, using the OLS residuals of first-differenced model and spatial weights, we conduct Lagrange Multiplier (LM) tests for spatial error autocorrelation and spatial lag dependence.

The LM tests suggest that the spatial error model better fits the data (Table 4). The LM error test is statistically significant for the revised first-differenced model. The Moran's I is 4.908 and statistically significant, and both LM and robust LM error tests are significant (Table 4, column 5). For this reason, we initially estimate a spatial error model. For comparison purposes (and for purposes of robustness), we also estimate a spatial lag model.

4.7 Results from the Spatial Econometric Models

The estimates of the coefficients produced by the spatial econometric models confirm that a positive spatial correlation exists in the data (Table 5). The spatial autoregressive coefficient λ is positive (0.427) and is highly significant (standard error is 0.117) for the spatial error model (Table 5, column 1). In the meantime, the spatial autoregressive coefficient ρ is positive (0.319) and significant (standard error = 0.118) for the spatial lag model (Table 5, column 2). These results suggest that any analysis of forest cover change using spatially

Table 4 Monte Carlo results for diagnoses on the spatial error/lag problems for forest cover change

	Dependent variable: *Forest cover change*
Moran's I	4.908
	(0.00)
LM (error)	21.947
	(0.00)
Robust LM (error)	22.075
	(0.00)
LM (lag)	10.608
	(0.07)
Robust LM (lag)	10.736
	(0.03)
Observations	2,614

p Value in parentheses

explicitly GIS-based data in Sichuan province needs to consider the effects of the spatial error and/or the spatial lag components. Moreover, the positive and significant coefficient in the spatial lag model (ρ) suggests that forest management decisions have a positive association with neighboring areas. In other words, if a forest patch is harvested, its neighboring pixel is also likely to be harvested and vice versa.

Importantly, the estimate of coefficient on GDP per capita remains negative and statistically significant in both spatial error and spatial lag models (Table 5, columns 1 and 2). In addition, the coefficient of GDP per capita squared remains positive and significantly different from zero in both the spatial econometric models. The regression coefficients for both the linear and the quadratic terms are slightly larger in absolute value compared to the first-differenced model. The magnitude of the changes may due to the different nature of the relationship between the dependent variable and GDP per capita in the spatial econometric models.

Based on the estimated coefficients of GDP per capita and GDP per capita squared variables in the spatial error model, the turning point of the EKC for forest in Sichuan is about 399,520 Yuan ($48,251). The real GDP per capita in Sichuan in 2008, however, was only 8,767 Yuan (US$ 1,059), which is much lower than the turning point. In other words, according to our findings, it is going to take more than 40 years for Sichuan's GDP per capita to reach the turning point even if the economy continues to grow at a 10% annual growth rate. Therefore, based on the estimated EKC parameters, the forests in Sichuan will keep decreasing for more than 40 years until the GDP per capita level reaches the turning point (assuming nothing else changes and assuming that there is no effective forest policies that are used to intervene in this trend). The high turning point can also be interpreted that there may not be an EKC—at least in the relevant range of our current analysis). When we create a scatter plot the observations, most pixels are located in the down-sloping part and only a few pixels are on the right hand side of the U-shaped shape. This finding suggests that forest policies may be necessary in order to control and slow the process of forest decline in the coming years (which will also end up, if successful, in flattening the EKC).[11]

[11] As a robustness check, we examined whether the model produces estimates of income elasticity that are significantly different from zero. To do so, we ran a pooled cross-sectional model and a first-differenced model without the quadratic term. When running the cross-sectional model, the estimated coefficient on the GDP

Table 5 Monte Carlo estimates of spatial error/lag model

	Dependent variable: *Forest cover change*	
	Spatial error model	Spatial lag model
Δ GDP per capita	−1.678	−1.671
	(0.530)	(0.530)
Δ (GDP per capita)^2	0.021	0.021
	(0.007)	(0.007)
Δ GDP per capita in 10 km buffer area	−0.325	0.091
	(1.168)	(1.039)
Δ Population density	−0.002	−0.002
	(0.002)	(0.002)
Δ Population density in 10 km buffer area	0.002	0.001
	(0.007)	(0.007)
Δ Distance to the nearest prefectural city weighted by GDP	0.001	0.001
	(0.001)	(0.001)
Δ Distance to the nearest urban core	0.071	0.050
	(0.083)	(0.060)
Δ Cultivated land in 10 km buffer area	−0.681	−0.608
	(0.147)	(0.135)
Δ Built-up area in 10 km buffer area	−0.329	−0.442
	(0.610)	(0.609)
Time trend (2000)	−0.151	−0.236
	(0.528)	(0.329)
λ or ρ	$\lambda = 0.427$	$\rho = 0.319$
	(0.117)	(0.118)
Observations	2,612	2,612

Absolute value of Huber-White robust standard error in parentheses

5 Conclusion and discussion

This paper examines the relationship between economic growth and forest resources in Sichuan province, one of the largest, most forested provinces in China. We found a statistically significant U-shaped relationship between the two. We used descriptive statistics, several different multivariate analyses and spatial econometric methods to identify this relationship. The estimated regression results provide evidence that there is a long run EKC for forest resources in Sichuan. However, the turning point is nowhere close. The estimated turning point of the EKC was 399,520 Yuan ($48,251). This level of income is far higher than the current average income level in Sichuan. Because of the short time interval of our data (from 1995 to 2000), the findings may be too fragile (and out of the predictive range of the findings).

Footnote 11 continued
per capita variable is −0.007 which is significant at the 5% level. The estimated coefficient on the GDP per capita variable from the first-differenced model (without the quadratic term) is −0.033, which is significant at the 1% level. These results demonstrate that the model, in fact, does produce estimates of income elasticity that are significantly different from zero.

It is probably safest to say that we were unable to produce strong evidence in favor the EKC in the case of forest resources in Sichuan.

This study illustrated importance in carefully modeling the relationship between economic growth and forest cover. As we moved from the basic model to increasingly sophisticated models, the parameters of interested continually change. This suggests that in analyses that do not account for unobserved effects, there are biases in the parameter estimates. The comparison between the estimated pooled cross-sectional model and first-differenced model shows that all fixed effects need to be controlled to get more precise estimates of our coefficients of interest.

The study also illustrated the importance of taking into account of spatial correlation in land use data. By employing a spatial error model, we estimated the relationship between economic growth and the forest cover change with more precision. In fact, when doing so, the level of significance and the magnitude of our estimated coefficients changed. The implications of this is that without accounting for spatial effects we would have over- or under-estimated the effects of certain explanatory variables on the forest cover change.

Most importantly, our findings about the U-shaped relationship between forest resources and GDP per capita suggest that Sichuan is still in the first stage of economic growth. Therefore, policy makers in China need to prepare themselves for the task of creating policies that will be needed to slow down or to reverse the trend of declining forests. In fact, China's government is taking steps in rebuilding China's forest cover and stock as exemplified by two large-scale policies: the Natural Forest Protection Plan, which includes a logging ban on state-owned forests, and the Sloped Land Conversion Program (also known as the Grain for Green program), which gives compensation to farmers who retire sloped land from agriculture and plant tree seedlings. Continued economic growth—at least in the near future—is not the answer.

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Appendix

see Table 6.

Table 6 Descriptive statistics of variables for the sampled data

Variable	Unit	Mean	SD	Minimum	Maximum
Forest cover in 1995	%	28.88	32.17	0.00	100.00
Forest cover in 2000	%	29.38	31.01	0.00	100.00
GDP per capita in 1995	10,000 Yuan	0.42	4.14	0.00	754.69
GDP per capita in 2000	10,000 Yuan	0.55	4.85	0.00	842.63
GDP per capita squared in 1995	10,000 Yuan	17.27	2,036.14	0.00	$5.69 * 10^5$
GDP per capita squared in 2000	10,000 Yuan	23.75	2,552.44	0.00	$7.10 * 10^5$
GDP per capita in 10 km buffer area in 1995	10,000 Yuan	0.28	0.36	0.00	19.84
GDP per capita in 10 km buffer area in 2000	10,000 Yuan	0.37	0.43	0.00	21.06
Population density in 1995	Person/km^2	363.67	607.37	1.00	26,141.00
Population density in 2000	Person/km^2	388.34	709.01	1.00	37,008.00
Population density in 10 km buffer area in 1995	Person/km^2	343.81	345.34	0.00	6,666.93

Table 6 continued

Variable	Unit	Mean	SD	Minimum	Maximum
Population density in 10 km buffer area in 2000	Person/km^2	366.19	377.46	0.01	7,960.90
Distance to the nearest prefectural city weighted by GDP in 1995	km	2,655.09	2,566.72	0.00	20,027.40
Distance to the nearest prefectural city weighted by GDP in 2000	km	2,683.76	2,801.79	0.00	21,624.08
Distance to the nearest expressway	km	28.72	23.78	0.00	134.00
Distance to the nearest provincial way	km	30.96	22.77	0.00	124.00
Distance to the nearest other roads	km	6.02	6.66	0.00	49.00
Distance to the nearest local road	km	3.63	3.74	0.00	37.00
Distance to the nearest forest in 1995	km	1.61	2.18	0.00	21.21
Distance to the nearest forest in 2000	km	1.51	2.03	0.00	19.65
Distance to the nearest urban core in 1995	km	22.89	16.63	0.00	126.02
Distance to the nearest urban core in 2000	km	22.24	15.67	0.00	126.02
Forest area in 10 km buffer area in 1995	%	29.72	23.30	0.00	99.97
Forest area in 10 km buffer area in 2000	%	31.34	22.43	0.00	96.25
Cultivated land in 10 km buffer area in 1995	%	53.75	30.95	0.00	100.00
Cultivated land in 10 km buffer area in 2000	%	52.38	30.06	0.00	99.82
Built up area in 10 km buffer area in 1995	%	1.01	3.24	0.00	63.13
Built up area in 10 km buffer area in 2000	%	1.24	3.56	0.00	66.56
Average elevation	m	1,095.33	912.64	0.00	4,696.00
Average slope	Degree	5.23	5.71	0.00	44.59
Average precipitation	mm	1,059.58	167.28	321.20	1,828.90
Average temperature	Degree	13.94	3.44	−3.60	21.20

Absolute value of Huber-White robust standard error in parentheses

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