INVESTIGATING IMPACTS OF ECONOMIC GROWTH ON THE ENVIRONMENT

USING REMOTE SENSING TOOLS: A CASE STUDY OF GROSS DOMESTIC

PRODUCT AND NET PRIMARY PRODUCTION

IN CHINA FROM 2001 TO 2007

by

Naizhuo Zhao, B.S., M.S.

A dissertation submitted to the Graduate Council of
Texas State University in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
with a Major in Environmental Geography
August 2014

Committee Members:

Nathan Allen Currit, Chair

Christopher D. Elvidge

Jennifer Jensen

F. Benjamin Zhan

ACKNOWLEDGEMENTS

I want to express my greatest gratitude to my dissertation advisor, Dr. Nate Currit for his insightful guidance and constant encouragement. I would also like to thank my outstanding committee members: Drs. Christopher Elvidge, Jennifer Jensen, and Benjamin Zhan. I am very grateful for their insightful comments and careful review of my proposal and dissertation.

Additionally, I would like to extend my gratitude to Drs. Tilottama Ghosh and Xingjian Liu for their well-considered suggestions in my nighttime-light-imagery and other relevant scientific studies. Special thanks go to my friend, Dr. Eric Samson, not only for help to improve my English writing skills but also for enthusiastic suggestions to make me live and study better in the United States.

Finally but most importantly, I want to express my deepest appreciation to my wife, my parents, my grandfather, and my aunts for their unconditional love and consistent support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Pursuing sustainable co-development of economy and environment has been established as a basic national policy by the present Chinese government. However, studies regarding actual outcomes of the co-development policy at the whole Chinese scale are still limited. Detecting China's economic growth and changes of environmental quality will not only contribute to evaluation of outcomes of the co-development policy but more importantly is an opportunity to examine the suitability of the IPAT model and improve our understanding of human-environment interactions. The core of the IPAT theory is an equation where $I=P \times A \times T$ that models human impact on the environment as a function of changes to population (P), affluence (A), and technology (T). The IPAT theory emphasizes that economic growth will inevitably produce negative impacts on the environment. Thus, if China's environmental quality declined while economic growth occurred, then the IPAT theory will be substantiated. Otherwise, the suitability of the IPAT theory will be called into question and its tenets must be reconsidered.

In this dissertation research I selected gross domestic product (GDP) and net primary production (NPP) as indicators to evaluate production of social and ecological systems respectively. The main study objectives are (1) to develop a methodology to facilitate integration of the two indicators derived from demographic data sources and satellite imagery at different geographic scales, (2) to jointly explore changing patterns of

China's economic and ecological production (i.e., spatially and temporally coincident patterns of change in GDP and NPP) across different spatial scales, (3) to analyze whether economic growth has produced negative impacts on ecosystem production and whether the impacts correlate to the economic growth, and finally (4) to discuss whether the IPAT theory is suitable for explaining the joint changes of GDP and NPP in China or if it is in need of modification. To fulfill the study objectives, nighttime light images and LandScan gridded population data were used to disaggregate demographic GDP data reported at the province level to the pixel level. The disaggregated GDP data were integrated with MODIS annual NPP data to map joint changes of GDP and NPP from 2001 to 2007. Economic development and environmental change can lead to land cover change, and the land cover change can, in turn, determine the changes of NPP. Thus, a change detection matrix with basic land cover elements was produced from MODIS land cover type products to augment the analyses of changing patterns of GDP and NPP in China. To safely discern that the changes of NPP are mainly affected by anthropogenic factors and not natural forces, the extents of undeveloped, established developed (existing before 2001), and newly developed (emerging after 2001) areas were delimited from the nighttime light images.

Results show that most Chinese developed areas experienced coupled increases in GDP and NPP between 2001 and 2007 across different geographic scales, but no

significant correlations exist between the total changes (or percentage changes) in GDP and NPP at the province, the city, or the pixel level. Despite large increases in GDP, the decreases in vegetated land expected according to IPAT theory did not occur in developed areas. Instead, barren land markedly decreased and built-up land slightly decreased in extent. These changing patterns suggest that China's economic growth produced some positive impacts on its ecosystem production as measured using NPP. In light of these findings a reexamination of the IPAT theory is necessary. I propose a revision to the Environmental Kuznets Curve (EKC) concept to fully illustrate the relationship between economic growth and ecosystem production as an indicator of environmental quality. According to the EKC, at relatively low levels of economic output, economic growth produces negative impacts on environmental quality. The negative impacts tend to reach a maximum at high levels of economic output and then decline at sustained levels of high economic output. My findings indicate that at sustained levels of high economic output some negative impacts may be reduced, but that some positive impacts may simultaneously emerge.

I. INTRODUCTION

Modern geography emphasizes that human systems and environmental systems are interdependent (Leichenko and O'Brien, 2008; Turner, 2002). Separately considering human and environmental systems may appear to strengthen our understanding of a single sub-system but leads to a reductionist view of the whole system (Walker and Salt, 2006). Thus, it is necessary to analyze human systems and environmental systems jointly (Parker et al., 2003; GLP, 2005; Levin, 1998).

As the largest developing country in the world, China's economic growth and environmental change have greatly affected the global economy and the entire Earth system (Keng, 2006; Liu and Diamond, 2005; Lo, 2002; Piao et al., 2009). Since Deng Xiaoping implemented economic reform in 1978, China has achieved substantial economic growth, but the overall state of its environment has progressively deteriorated (Liu et al., 2008; Liu and Diamond, 2008). China's environmental problems have seriously affected people's lives and impeded sustainable economic growth (Liu et al., 2008). China's present government has therefore decided to pursue sustainable co-development of the economy and the environment as a fundamental national policy.

Exploring changes of China's human-environmental systems in the 2000s provides an opportunity to test the IPAT theory. The IPAT theory asserts that economic growth inevitably generates adverse impacts on the environment (Chertow, 2000; York et al., 2003). If China's environmental quality declined during the economic growth of the 2000s, the IPAT theory would be reinforced. However, if China achieved co-development of the economy and the environment, or even if China had fewer negative environmental impacts accompanying economic growth, it would be necessary to doubt the suitability or applicability of the IPAT theory. But, due to a lack of practical studies regarding China's human-environmental systems in the 2000s, it is still not clear what the actual outcomes of co-development are. The challenge of collecting high resolution, up-to-date data for such a large area may partly explain the lack of practical studies. It is essential, therefore, to collect and process huge and diverse spatial datasets from the human and environmental systems for the 2000s. Performing such a comprehensive human-environmental study at a sufficiently detailed resolution, however, is not a trivial task using traditional census-based methods.

Remote sensing is a powerful tool with an extensive record of successful application to natural systems research covering large areas. A number of satellite image products (e.g. the Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices, MODIS Gross Primary Productivity (GPP), MODIS Land Cover Type, and the Advanced Very High Resolution Radiometer (AVHRR) Summed Annual Global Net Primary Production (NPP)) were developed and released freely in recent years and such products greatly facilitate studies of environmental systems (Global Land Cover Facility, 2011; USGS, 2011a).

Compared to the image products developed to monitor environmental systems, there are fewer image products that can be used to evaluate human systems (Jensen et al. 2002). The Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) nighttime light imagery has proven to have potential to calculate socioeconomic parameters (e.g. electric power consumption, fossil fuel carbon dioxide emission) (Amaral, et al., 2005; Elvidge, et al., 1997a; Oda and Maksyutov, 2011; Ghosh et al., 2010a), and is especially effective for estimating gross domestic product (GDP) at national and sub-national levels (Doll et al., 2000; Doll et al., 2006; Ghosh et al., 2009a; Ghosh et al., 2009b; Ghosh et al., 2010b; Lo, 2002; Sutton et al., 2007).

Despite advances in the application of remotely sensed data and analysis techniques for studying human and environmental systems independently, the integration of spatial information collected by different remote sensors for practical studies of joint human-environmental systems is a major deficiency at the present time (GLP, 2005). One particular challenge to this integration is the scale mismatch between satellite pixel resolution and the aggregation of census data. For example, MODIS and DMSP-OLS image products have an approximate resolution of 1 km, but for most developing countries, and for China in particular, socioeconomic data is usually surveyed, processed, and recorded at the national and regional levels. The result is that estimation of socioeconomic parameters using the DMSP-OLS nighttime imagery is done mostly at the national and regional levels. Thus, a major challenge of integrating the DMSP-OLS nighttime images with other environmental remote sensing image products is the need to disaggregate nighttime-image-estimations from the national/regional level to the pixel level.

The IPAT theory suggests that environmental impacts are the product of interactions between population (P), affluence (A), and technology (T). Growth of population and affluence will both produce negative impacts on the environment (Chertow, 2000). GDP is a basic indicator of a region's economic and living conditions. Affluence is typically measured by GDP per capita (York et al., 2003), so GDP is a product of affluence and population. Thus, based on the IPAT theory an increase in GDP should lead to a decline in environmental quality. NPP – the accumulation of primary biomass – is not only an important quantitative factor in research of the global carbon cycle but also represents the amount of primary food energy in natural systems (Imhoff et al., 2004; Zhao and Running, 2010). NPP can reflect an environmental system's quality and its ability to produce ecological goods and service. Consequently, the IPAT theory suggests that increases in GDP should lead to decreases in NPP, particularly in areas where stable socioeconomic activities exist. Many previous studies have shown that GDP and NPP can be estimated by remotely sensed data separately (Doll et al., 2000; Prince and Goward, 1995; Sutton et al., 2007; Zhao et al., 2005), but few studies have attempted to integrate remote-sensing-derived GDP and NPP for analyzing or solving practical problems. Additionally, population growth and economic development may lead to land cover changes as results of deforestation, grassland degradation, urban sprawl etc. (Lambin et al., 2001; Mather and Needle, 2000; Meyer and Turner, 1992). With rapid development of its economy and a pattern of urbanization, China has experienced tremendous land cover changes (Hubacek and Sun, 2001; Liu et al., 2003; Liu and Tian, 2010), and the land cover changes have been recorded by remote sensing imagery (Friedl et al. 2002; Justice et al., 2002).

In this study, I integrate GDP and NPP data from traditional census and remote sensing platforms to explore the outcomes of China's co-development strategies on production of human-environmental systems. The integration results in a methodology to downscale socio-economic indicators from the province level to the pixel level and thus allows the joint analysis of human-environmental systems across different geographic levels (national, province, city, and pixel levels). This analysis focuses on the impacts of economic growth (i.e., increase in GDP) on ecosystem production (i.e., NPP) and land cover change, and consequently examines the suitability and applicability of the IPAT theory in China during the period in which co-development policy was implemented.

II. LITERATURE REVIEW

China's human and environmental systems

The Chinese economy has experienced high and unbalanced growth in the last thirty years (Keng, 2006; Liu et al., 2008). During this time, China maintained an annual economic growth rate of approximately 10%, which is the fastest among major global economies (Liu et al., 2008). However, Chinese economic development created regional disparities that manifested themselves in production agglomerations in coastal regions and large income gaps between the coastal regions and the interior (Fujita and Hu, 2001). The production agglomerations resulted in rapid economic development in the coastal regions, but slow economic growth in western regions and a fast decline in the economic status of northeastern regions. Specifically, ten regional economic agglomerations emerged in China, six of which are located in coastal regions (Liaoning Peninsula, Capital, Shandong Peninsula, Greater Shanghai, Fujian, and Pearl River Delta) and four of which are located in inland regions (Jilin-Heilongjiang, Yangtze River Downstream, South-Central, and Sichuan Basin) (Keng, 2006). The unbalanced economic growth led to tremendous migration. A large number of western and central people were attracted by favorable jobs in the coastal regions (Liang, 2001). To overcome the increasingly large regional disparities, the Chinese government implemented several regional economic programs (e.g. Development of West China and Revitalizing Northeast Old Industrial Base) (Lai, 2002; Zhang, 2008).

Protection and development of Chinese environmental systems were neglected early in China's economic reform when the Chinese government concentrated on improving overall economic well-being and per capita incomes (Liu and Diamond, 2005). Since the economic reform started in 1978, China played an increasingly active role in international trade. A large number of natural resources were depleted in the production of export goods (Liu, 2010). Additionally, rapid urban sprawl accompanied the exceptional economic growth. Large areas of forests, grasslands, and agricultural lands were converted to built-up lands. Deforestation, grassland degradation, and arable-land loss lead to declines in ecosystem yield, and are consequently reflected by changes in NPP. The environmental degradation has led to emerging serious natural hazards and huge economic losses in China (Liu et al, 2008). It is widely believed that the massive floods in 1998 were the result of deforestation and soil erosion (Liu, 2010; Liu et al., 2008). The devastating natural hazards and massive economic losses made the Chinese government recognize that ecological protection can guarantee and promote sustainable economic development, and consequently a set of large-payment, long-term, and large-scale environmental protection programs were implemented by the Chinese government (e.g. the Natural Forest Protection Program (NFPP), the Sloping Land Conversion Program, and the Grain to Green Program (GTGP)). The main aim of the programs is to prevent forestlands and grasslands from being destroyed due to commercial purposes (Xu, et al., 2000; Xu, et al., 2006). Meanwhile, many environmental protection laws and policies were enacted, but Liu (2010) and Liu and Diamond (2008) believe that few of them were implemented effectively.

In the 2000s, the Chinese government completely replaced previous policies that viewed ecological resources as the sole means to economic growth with a policy of sustainable co-development. The co-development policy requires local governments to coordinate the relationship between environmental quality and economic development, restrain environmental deterioration, and improve the ecological situation (Geng, 2011). After undergoing a more than thirty-year accumulation of economic growth (from the 1978 economic reform onward), the Chinese government has had adequate money to compensate and remedy the environmental losses generated by the previous economic development practices. After meeting their basic needs, China's ordinary citizens now have a higher expectation for their quality of life and environment and, consequently, they demand government efforts to strengthen environmental systems. More importantly, the Chinese government enacted more stringent laws and policies to protect the environment (Geng, 2011). Environmental protection has been regarded as an essential criterion of economic growth to evaluate local government officials' performance and promotion (Zhou, 2002). It is highly possible that changing patterns of production of Chinese human-environmental systems in the 2000s are different from those in the 1990s and the 1980s. Therefore, although Liu et al. (2008) have evaluated changes of Chinese human-environmental systems in the 1980s and the 1990s, it is still necessary to re-examine the impacts of China's economic growth on its ecological production in the 2000s.

Human-environment interaction and IPAT theory

The study of human-environment interaction is a tradition of geographic studies (Pattison, 1964). Turner (2002) even argued that the human-environment is the subject of geography rather than space-time. Early human-environment theories maintained that relationships between humans and the environment were unidirectional. As a precursor to contemporary human-environment theories, Malthus (1798, reprinted in 2013) argued that population growth outpaces resources growth. He asserted that to avoid depletion of resources, war, famine, disease and other forms of population control would inevitably arise to reduce the pressure on resources. Malthus's theory influenced Darwin's theory of natural selection (1859). Darwin suggested that individuals of a species being produced were always more than those being supported by limited natural resources and consequently competition for survival between individuals emerged. Malthus's and Darwin's theories were accepted by most geographic scholars such as Friedrich Ratzel (1844-1904), Ellen Churchill Semple (1863-1932), and Ellsworth Huntington (1876-1947) between 1870 and 1950. Hence, prior to the 1950s, a major intellectual current regarding the human-environment was environmental determinism (Mairs, 2007). Environmental determinism emphasized that human society was limited by environmental factors.

Modern geography often treats human systems and environmental systems as adaptive and interactive systems, emphasizing feedback loops as opposed to unidirectional linear causalities in human-environment research (Moran, 1982). Human systems and environmental systems are adaptive because they have feedback structures maintaining their basic functions in constantly changing environments (Walker and Salt, 2006). Interactions between humans and the environment are not as unidirectional and linear as environmental determinism asserted—humans modify the environment for their survival. Although environmental systems have adaptive capacities to maintain or restore their original functions when confronted with human perturbations or natural distrubances, they may lose their original attributes and convert to new, unexpected and uncontrolled systems once the perturbance is larger than certain thresholds (Walker and

Salt, 2006). Human's excessive perturbances have led to some environmental systems losing functions that regulate climate and consequently extreme climates occurred increasingly frequently on the earth (Hulme et al., 1999; Min et al., 2011). Consequently, humans have to adapt to new environmental conditions with more extreme climates by, for example, moving to higher-altitude regions or building levees in response to sea-level rise. That these activities have occurred is evidence that humans are able to adapt to new environmental conditions just as the environment can influence human actions and behaviors. Thus, human systems and environmental systems are interactive and co-adapted.

Although many modern geography theories (e.g. resilience, adaptation, double exposure) have highlighted theoretical methods of studying human-environment interactions (Holling, 1973; Leichenko and O'Brien, 2008; Walker et al., 2004), few of them explicitly clarify quantitative correlations between human activities and the activities' environmental impacts like the IPAT theory does. The IPAT theory suggests that environmental impacts (I) are the product of interactions between population (P), affluence (A), and technology (T) (Chertow, 2000). The I=PAT equation was born from a debate between Commoner (1971; 1972), and Ehrlich and Holdren (1971) and subsequently has been developed by many environmentalists, ecologists, and economists to be a comprehensive theory to assess impacts of human activities on the environment (York et al., 2003). Commoner (1971; 1972) argued that technology was the principal reason leading to changes in environmental quality while Ehrlich and Holdren (1971) emphasized that population growth inevitably resulted in environmental degradation despite progress in technology. At present, scholars nearly unanimously accept the view that the population, affluence, and technology jointly impact the environment (Alcott, 2010). Specifically, most environmentalists and ecologists agree with three basic points of view in the IPAT theory:

(1) Increased population increases human's negative environmental impacts.
(2) Increased affluence increases human's negative environmental impacts.
(3) Increases in efficiency (increases in technology) reduce human's negative environmental impacts.

The IPAT theory has been applied to study human impact on greenhouse gas emissions and climate change for the last twenty years, even though some of the studies obtained results inconsistent with the basic tenets of the IPAT theory. Dietz and Rosas (1997) found that impacts of affluence on CO_2 emissions reached a maximum at about $10,000 per capita and declined at higher levels of affluence. Grossman and Krueger (1995) found no evidence supporting a relationship between economic growth and decline in environmental quality. Martinez-Zarzoso et al. (2007) found population significantly impacted CO_2 emissions and population produced higher negative environmental impacts in less developed regions. Roberts and Grimes (1997) found that in the 1960s and 1970s there were positive linear relationships between affluence and technology (i.e. larger GDP per capita and larger CO_2 emission per unit of GDP). However, in the 1980s and 1990s relationships between affluence and technology were best described as inverted-U curves. In other words, CO_2 emissions per unit of GDP first increased as GDP per capita increased, then beyond a threshold, CO_2 emission per unit of GDP decreased with further increases in GDP per capita.

The previous studies show that increases in population and affluence do not always lead to increases in negative impacts on the environment. Explanations about the relationships between increases in population and affluence and decreases in discharge of pollutants can be considered with two scenarios: (1) at high levels of average income, production is more efficient which results in an overall reduction in pollution and (2) at high levels of average income residents have higher requirements for their quality of living environment and object to the existence of polluting firms (Keen and Deller, 2013). Kuznets (1995) synoptically described relationships between economic growth and environmental degradation using an inverted-U curve that was subsequently named the environmental Kuznets curve (EKC). The EKC shows that negative environmental impacts first rise with economic growth, but after income per capita reaches a threshold value the negative environmental impacts are reduced with further economic development. After experiencing more than thirty years of economic growth, China's overall economy has reached a relatively high level. Thus it is time to re-test whether recent economic growth in China continues to negatively impact the environment, particularly after co-development has been implemented.

In this dissertation I explore the impact of China's economic growth on its environment across different geographic scales in the 2000s. Human activities can influence various aspects of the environment such as water quality, air quality, biological habitats, etc. In this study I select NPP and land cover as indicators of the environment because NPP and land cover can directly impact global and regional climate (Chase et al., 1999; Houghton et al., 1999), biodiversity (Sala et al., 2000), soil degradation (Tolba et al., 1992), and the ability of ecosystems to support human needs (Imhoof et al., 2004; Vitousek et al., 1997).

Demographic data for China's human systems are mainly reported at the province or regional level. To integrate these data with environmental remote sensing data and then examine human's environmental impacts at different geographic scales, the demographic data need to be spatially disaggregated to finer spatial levels. In this study the spatial disaggregation is accomplished using nighttime light imagery.

The DMSP-OLS nighttime imagery

Products

In this study I will use DMSP-OLS nighttime light images, one of the most powerful remote sensing tools for monitoring social systems, to spatially disaggregate GDP and integrate with MODIS NPP. In the following section, I will review strengths and limitations of DMSP-OLS nighttime imagery and introduce major applications of the nighttime lights imagery, particularly joint applications of the nighttime lights imagery and environmental remote sensing imagery.

The DMSP is a Department of Defense program started in 1972 and run by the Air Force Space and Missile Systems Center. OLS is the sensor onboard DMSP satellites which images the entire global surface twice a day from 830 km above the earth surface with 3000 km wide swaths in visible and near infrared spectral bands (0.4-1.1μm). DMSP/OLS was initially designed to collect information about moonlit clouds (Doll, 2008), but Croft (1973) first exploited the potential of the DMSP/OLS nighttime imagery for civilian research by mapping human settlements and production activities.

During early use of nighttime images, the challenge of separating stable light from ephemeral light became an issue. To overcome this problem, Elvidge et al. (1997b) developed an algorithm to produce light-frequency image products. On the light-frequency image products, each pixel's digital number (DN) is the number of cloud-free detected lights divided by the total number of cloud-free observations and then multiplied by 100. Thus, DN values represent the frequency of detected lights, but not brightness. As might be expected, the pixels with high frequency of occurrence are stable light sources while those with low frequencies are ephemeral light sources. The main problems with this type of image are (1) the relatively small spatial extent of the detected lit areas and (2) the large number of pixels from urban centers with the highest possible DN value (i.e., 100) (Doll 2008). In regard to these problems, Elvidge et al. (1999) developed another algorithm to produce radiance calibrated image products. High (50dB) and a low (24dB) gain values were used to detect light. High and low gain value composites were weighted respectively by their total numbers of detections and averaged to produce final radiance calibrated images. In 2010, the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center (NGDC) released a new version of the radiance calibrated image product, which is composed of high, medium, and low gain value images. Although there are no saturation pixels in the radiance calibrated image products, NOAA's NGDC only produces and releases two annual radiance calibrated image products (the old version for 1996 to 1997 and the new version for 2006) due to difficulty of selecting appropriate gain values and complexity of production procedure.

At present, the most widely used DMSP-OLS nighttime light image products are averaged digital number image products. NOAA's NGDC produces and releases two versions (Version 2 and Version 4) of time series annual digital number image products. There are two separate annual image products derived from two satellites for most years to avoid degradation of data quality due to aging of the satellites/sensors (Elvidge et al. 2009b). One of the major drawbacks in the digital number image products is that a certain number of saturation pixels may decrease the quality of socioeconomic parameter predictions (e.g. GDP and electric power consumption) (Chand et al., 2009; Doll, 2008; Sutton et al., 2007). Compared to the Version 2 image composites, the Version 4 stable lights annual image composites cover more years and have fewer saturated pixels (Table 2.1). Therefore, I will select the Version 4 nighttime image products to estimate GDP in this study.

Table 2.1. Percentages of the saturation pixels to lit pixels for Version 2 (V2) and Version 4 (V4) image products. Image data for 1995, 2000, and 2003 were collected by satellites F12, F14 and F15 respectively.

Year	V2-1995	V2-2000	V2-2003	V4-1995	V4-2000	V4-2003
US	0.0264	0.0284	0.0279	0.0199	0.0203	0.0147
China	0.0031	0.0026	0.0048	0.0025	0.0012	0.0020
World	0.0128	0.0131	0.0120	0.0100	0.0093	0.0065

Applications

The DMSP-OLS nighttime imagery has been proven to be a powerful tool to monitor and evaluate social systems. Croft (1973) and Welch (1980) first recognized the potential of the DMSP-OLS nighttime images to map human settlement. After NOAA released the frequency detection nighttime image products, nighttime image data can be used quantitatively to estimate population metrics. Sutton et al. (1997) tried to establish a relationship between the DN value of the nighttime imagery and population density for the United States. However, the results showed that the correlation was not very strong. Sutton et al. (1997) believed that the limited spectral or spatial resolutions may be the main reason leading to the actual correlation being not as strong as expected. A city's brightness of lights at night is not only dependent upon population density but also upon economic level. A region with increased business activity usually has brighter light at night than a region with less-developed business activity though they may have nearly the same population density. Hence, I think the uncertain factor of economic development level may be another factor that reduces the quantitative correlation.

Although DN value of nighttime imagery is not a good proxy to predict population density, several studies have been accomplished using lit area (the areal extent of lighting) to estimate urban population. A relationship between the area of a city and its population was identified by Stewart and Warntz (1958). The areal extents of cities can be delimited from the nighttime images by setting up thresholds of DN value (Imhoff et al., 1997b; Sutton et al., 2010). Regression models to predict the United States (Sutton et al., 1997), Chinese (Lo, 2002), Australian (Sutton et al., 2010) and global (Sutton et al. 2001) urban population have been developed using the nighttime images and based on the relationship of the size of a city and its population. Sutton et al. (2007) believed that 30 is a relatively appropriate threshold of DN value for the Version 2 nighttime image to delimit urban extents of the United States, but this value is not appropriate to delimit other countries' urban extents (e.g. 10 for Australia) (Sutton et al., 2010). However, Imhoff et al. (1997b) believed that even for one country, there is not a single, uniform threshold of DN value for all the individual cities. In order to precisely delimit individual cities' extents, ancillary remote sensing data (e.g. TM, MODIS, and SPOT) are needed in conjunction with the nighttime images (Gallo et al., 2004; Lu et al., 2008; Cao et al., 2009).

During the early use of the DMSP-OLS nighttime imagery, sum light and lit area were proxies that were extracted from the nighttime images to estimate GDP, energy consumption, and greenhouse gas emissions on the national and regional levels (Doll et al, 2000; 2006; Elvidge et al., 1997a; Lo, 2002). Sutton et al. (2007) employed the LandScan population dataset to augment the nighttime image data to estimate GDP on the regional level. In Sutton et al's (2007) method, urban extents were first delimited by the areal extent of lighting. Population located in the urban extents was extracted from the LandScan population dataset as urban population. Urban population has a significant correlation with GDP, and lit area has a significant correlation with urban population. So, lit area can be used to estimate GDP via urban population as an intermediate variable. The results showed that the estimate accuracy with urban population as an intermediate variable is far higher than those directly using linear correlations between GDP and lit area or sum light. However, previous versions of the LandScan population dataset are not recommended for use by the Oak Ridge National Laboratory (2010b), because there are more errors in the previous versions. Thus, it is a challenge to use the present version LandScan population dataset in conjunction with the annual nighttime image composites to estimate GDPs for different years and make an inter-comparison.

Inter-calibration and spatial disaggregation

After NOAA's NGDC released Versions 2 and 4 time series annual digital number image products, scholars can use nighttime light imagery data to quantitatively evaluate spatio-temporal changes of anthropogenic systems. Chand et al. (2009) and Townsend et al. (2010) used a set of annual nighttime image composites to monitor changes of electric power consumption in India and Australia respectively. Zhang and Seto (2011) employed multi-temporal Version 4 annual images to map urbanization. However, they all neglected an essential problem: the incompatible DN value among the annual nighttime image composites. Without particular pre-processes to the multi-temporal annual nighttime image composites, we cannot ascertain whether changes in DN values are due to changes in brightness of ground lights or gain values of the sensors (Doll, 2008). The OLS lacks an on-board calibration system, which makes calibration of the DN value difficult. Elvidge et al. (2009b) developed a set of empirical regression functions for inter-calibrating version 2 nighttime imagery products. This work greatly contributes to the literature of using nighttime images to quantitatively evaluate temporal changes of social system.

Although DMSP-OLS nighttime imagery has a moderate spatial resolution (1 km), most previous estimates of GDP, electric power consumption, and/or greenhouse gas emission were completed on the national or regional level because statistical data used for regression or calibration are usually reported on the national and regional levels (Chand et al., 2009; Doll et al., 2000; 2006; Elvidge et al., 1997a; Lo, 2002; Sutton et al., 2007). In recent years, Elvidge et al. (2009a) used DN values of the nighttime images to develop a pixel-level poverty index. Ghosh et al. (2010a) and Oda and Maksyutov (2011) disaggregated national fossil fuel carbon dioxide emission to pixels based on the pixels' DN value of the nighttime images. The spatial downscalings were carried out directly from the national level to the pixel-level in the studies. So a prerequisite to guarantee accuracy of the spatial disaggregation is that one DN value of the nighttime images should represent the same amount of wealth or fossil fuel carbon dioxide emission in a whole country. However, it can be expected that large variations in the amount of GDP represented by one DN value exist among different provinces and municipalities in China (e.g. 2.36 million yuan for Shanghai, and 0.89 million yuan for Xinjiang in 2007). Thus, large errors will be generated if GDP is directly disaggregated from the national level to the pixel level.

Combination of the nighttime images and environmental remote sensing images

The DMSP-OLS nighttime imagery itself is a powerful tool to estimate socio-economic parameters. Moreover, it is often combined with some environmental remote sensing image products, but the combinations are only for studying social systems. For example, Lu et al. (2008) combined the DMSP-OLS nighttime image data and MODIS NDVI data to map human settlements in China. Cao et al. (2009) used the DMSP-OLS nighttime imagery data and SPOT NDVI data to extract urban areas.

Zhao et al. (2011) combined the nighttime images and the AVHRR NPP images to study the interactions between Chinese social systems and ecological systems. The results revealed that economic growth generates adverse impacts on ecosystem production, but after the economy reaches a threshold level the adverse impact will begin to weaken. These findings are important and significant, but several things in that study need to be improved. First, the DMSP-OLS nighttime imagery is the only satellite data used to disaggregate GDP, so accuracy of the spatial disaggregation is not very high (Zhao et al., 2011). Second, the AVHRR NPP image product has a relatively coarse spatial resolution (8 km × 8 km). Third, the correlations between total changes in NPP and GDP were not analyzed by statistical methods, only by visual assessment. Finally, the study period is from 1996 to 2000 and does not correspond to the period of practice of China's co-development policies. During the period studied, the co-development policy was just implemented so the study did not evaluate the profound impacts of the co-development policy on Chinese human-environmental systems.

In the present study I used the Version 4 stable light annual image composites in conjunction with the LandScan population data to enhance the disaggregation accuracy of GDP at the pixel level. Additionally, I used the MODIS NPP product to replace the AVHRR NPP product because the MODIS NPP product has a finer spatial resolution (1 km × 1 km) than the AVHRR NPP product. More importantly, I statistically tested the correlations between total changes in NPP and GDP at the province and the city levels.

Working hypotheses

The IPAT theory suggests that economic growth will produce adverse impacts on the environment, and that quantitative correlations exist between economic growth and a decline in environmental quality. Many case studies (e.g. Dietz and Rosas, 1997; Grossman and Krueger, 1995; Harbaugh et al, 2002; Roberts and Grimes, 1997) found that the relationships between economic growth and declining environmental quality are nonlinear. The EKC shows that negative environmental impacts produced by economic growth begin to become increasingly smaller after the economy reaches a threshold. However, the EKC does not show whether some of the negative environmental impacts will be replaced by positive ones with continued economic development. Additionally, it is not clear whether quantitative relationships between economic growth and decline in environmental quality always exist with increasingly higher economic levels. To explore these scenarios and to better understand human-environment interactions across different geographic scales, I use remote sensing data to test whether coupled increases in Chinese social and ecological system's production (i.e., coupled increases in GDP and NPP) have occurred in the 2000s by testing for significant correlations between them. I propose the following research goals and hypotheses. My goals are (1) to develop a methodology for downscaling social variables from large census regions to the pixel level, (2) to integrate social and environmental variables derived from remotely sensed and demographic data sources in a way that will permit the analysis of joint changes in a human-environmental system across different geographic scales, (3) to explore the impacts of economic growth on ecosystem production and land cover change in China during the period of co-development policies, and finally (4) to analyze the applicability of the IPAT theory for explaining the relationship between economic growth and changes in ecosystem production. The specific hypotheses are:

(1) Nighttime lights imagery and the LandScan population dataset can be used effectively to downscale GDP to the pixel level to facilitate integration with environmental remote sensing products.

(2) At the province, city, and pixel levels, positive correlations exist between total changes (and percentage changes) in GDP and NPP in developed areas.

$H_{0\,prov,city,pixel}$: $\rho = 0$

$H_{A\,prov,city,pixel}$: $\rho > 0$

(3) At the city scale, developed and undeveloped areas have unequal percentage increases in NPP.

H_0: $\overline{\Delta\text{NPP}}_{dev} - \overline{\Delta\text{NPP}}_{undev} = 0$

H_A: $\overline{\Delta\text{NPP}}_{dev} - \overline{\Delta\text{NPP}}_{undev} > 0$

(4) With economic growth, vegetated land increases in area, and barren land and built-up land decreased in area.

H_0: $\overline{\Delta Area}_{vegetated,soil,built-up} = 0$

H_A: $\overline{\Delta Area}_{vegetated} > 0$

H_A: $\overline{\Delta Area}_{soil,built-up} < 0$

III. DATA AND METHODOLOGY

Data

Multiple data sources are required to meet the goals of this research. In particular, DMSP-OLS nighttime lights imagery, the LandScan global population dataset, Chinese GDP censuses, the MODIS NPP product, and the MODIS Land Cover Type product will be used in the analysis of coupled changes in GDP and NPP.

The version 4 DMSP-OLS stable light image products for the years 2001 and 2007 (F152001 and F162007) were taken from the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center (NGDC) (Earth Observation Group, 2010). Each annual stable light product is a composite of all the available cloud-free data for that particular calendar year in the NGDC digital archive. Ephemeral lights such as fires and lightning and other background noise have been removed. Digital number (DN) values of the nighttime image composites represent brightness and vary from 0 to 63 with a spatial resolution of 1 km^2. Detailed algorithms and processes for the products have been described by Elvidge et al. (1997b, 1999, 2009b) and Baugh et al. (2010).

The LandScan 2008 high resolution global population dataset was taken from the Oak Ridge National Laboratory. The population dataset is produced by interpolating sub-national census population data to fine spatial resolution with ancillary datasets like land cover, slope, and roads (Oak Ridge National Laboratory, 2010a). These ancillary datasets are derived from remotely sensed imagery (e.g. Landsat Thematic Mapper, MODIS, and Shuttle Radar Topography Mission (SRTM)). The population dataset has a 1 km × 1 km spatial resolution and DN values represent population counts. Accuracy of the Landscan population dataset was evaluated in the Southwest United States by comparing it with census data and was found to have 87.8% agreement with census data (Dobson et al., 2000). Detailed algorithms and processes for the dataset have been described by Dobson et al. (2000), Bhaduri et al. (2002), and Cheriyadat et al. (2007).

The improved MODIS annual NPP images (improved MOD17) for years 2001 and 2007 were obtained from the College of Forestry at the University of Montana (Numerical Terradynamic Simulation Group, 2010). The improved MODIS NPP images are the reprocessed MODIS NPP images created by NASA (MOD17). The essence of the algorithm of NASA's MOD17 product is an application of the radiation conversion efficiency logic to predictions of daily gross primary production (GPP), using the fraction of incident photosynthetically active radiation (FPAR) derived from MOD15 (MODIS Leaf Area Index (LAI) and FPAR image product). The maintenance respiration and growth respiration components estimated by MOD15 LAI are subtracted from GPP to obtain annual NPP (Running et al., 1999). There are a number of missing FPAR/LAI pixels in MOD15 due to the cloud contamination which leads to underestimations of GPP and NPP in MOD17 (Running and Zhao, 2010). In the improved MOD17, these contaminated MOD17 pixels have been cleaned to minimize the underestimation of NPP. The improved MOD17 agrees well with field measurement NPP data with correspondence of 77% (Zhao et al., 2005). The cell size of MOD17 is 1 km^2, and DN values represent the weights of carbon per square meter fixed by plants per year ($g\_C/m^2/yr$). Pixels with DN value of 65535 represent water, desert, and impervious surfaces. Detailed algorithms and processes for the improved MOD17 product are described by Zhao et al. (2005).

The MODIS land cover type (MCD12Q1) products for the year 2001 and 2007 were obtained from the USGS (2011b). Each MCD12Q1 product is produced by the combined image data collected by the MODIS sensors onboard the Terra and Aqua satellites, and describes land cover properties annually with 500 m spatial resolution. MCD12Q1 contains five sub-products (i.e. Land Cover Type 1 to 5) which are produced according to the International Geosphere Biosphere Programme (IGBP) global vegetation classification scheme, the University of Maryland scheme, the MODIS-derived LAI/fPAR scheme, the MODIS-derived NPP scheme, and the Plant Functional Type (PFT) scheme respectively. Although the MODIS land team does not report the accuracy for each land cover classification scheme of the MCD12Q1 product, it reports that the IGBP classification accuracy is estimated to be 74.8% with a 95% confidence interval as determined through comparison with *in situ* reference data or relatively high spatial resolution image data (e.g. Landsat data) (MODIS land team, 2009; 2011). The entire MCD12Q1 product is considered to be a validated Stage 2 product which means the various classification schemes are spatially and temporally compatible across different years. In the MCD12Q1 products land cover is classified mainly by supervised classification using approximately 2000 training sites around the world to train the classifier. Land-cover changes in the training sites is a major cause of errors and uncertainties in the MCD12Q1 products (Friedl and Sulla-Menashe, 2011). In this study, I select the Land Cover Type 4 using the NPP classification scheme because land covers in the Land Cover Type 4 sub-products are more easily re-classified into five main land cover types (i.e. water, forest, grass, barren land, and built-up land). In the Land Cover Type 4, there are nine land cover classifications: water, evergreen needleleaf vegetation, evergreen broadleaf vegetation, deciduous needleleaf vegetation, deciduous broadleaf vegetation, annual broadleaf vegetation, annual grass vegetation, non-vegetated land, and urban. As the name of the scheme suggests, land cover in the Land Cover Type 4 sub-products is classified mainly based on values of ground NPP. Detailed algorithms and processes for the product of the Land Cover Type 4 have been described by Running et al. (1994).

The statistical GDP data were obtained from the National Bureau of Statistics of China (2002; 2008) and reported by province/municipality (hereafter referred to as province). A municipality has the same administrative level as a province but a city has a lower administrative level than a province in China. In other words, a province is composed of several cities but never includes a municipality. The GIS boundary vector file (Figure 3.1) for China was acquired from the Digital Chart of the world of Environmental Systems Research Institute (ESRI) (Denko, 1992).

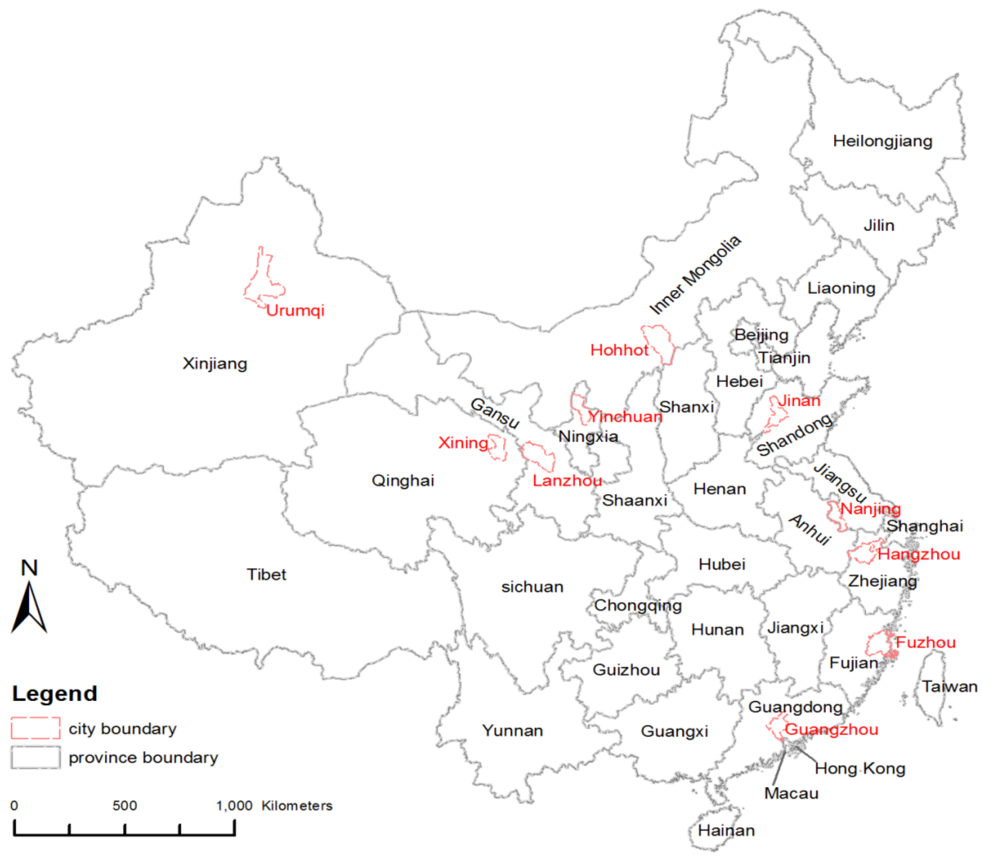

Figure 3.1. Administrative boundary map of China.

Methodology

Mapping GDP changes

The version 4 annual stable light image composites depict values in average digital numbers and are not radiometrically calibrated. Consequently DN values between the annual stable light image composites of 2001 and 2007 are incompatible (Doll, 2008, Zhao et al., 2012). Using Elvidge et al.'s (2009b) method, Liu et al. (2012) developed functions to inter-calibrate DN values of the annual stable light image composites for China. In this study, I applied the inter-calibration functions to make DN values in the multi-year nighttime light image composites compatible one with the other. The city of

Jixi in Heilongjiang province was supposed to have few changes in the lighting conditions from 2001 to 2007, and the 2007 image composite was selected as a reference image (Liu et al., 2012). A quadratic polynomial regression function (equation 1) was empirically developed via adjusting DN values of pixels in the region of Jixi from the 2001 annual image composite to match DN values of pixels in the region of Jixi in the reference image.

$$DN_{inter\text{-}calibrated\_2001}=0.9849*DN_{2001}+0.0019*DN^{2}_{2001}-0.4446 \qquad (1)$$

Then, this function was applied to the whole image to achieve an inter-calibrated image composite for 2001. After the inter-calibration, pixels with DN value of 0 in the original 2001 annual stable light image composite have DN values of -0.4446. To obtain correct lit area information, pixels in the inter-calibrated nighttime light image were revalued with function 2:

$$DN_{revalued} = \begin{cases} 0, & DN_{inter} \leq 0 \\ DN_{inter}, & DN_{inter} > 0 \end{cases} \qquad (2)$$

The revalued nighttime image composite of 2001 and the 2007 annual stable light image composite (hereafter referred to as nighttime light images of 2001 and 2007) were re-projected from Geographic coordinates to an Albers equal-area projection for extracting correct area information.

In order to show the fine scale spatial distribution of GDP, and more importantly to facilitate integration with MODIS NPP images, GDP obtained from the National Bureau of Statistics of China must be disaggregated from the province level to the pixel level. In previous studies, GDP (or other socioeconomic data such as electric power consumption and fossil fuel carbon dioxide emission) was spatially disaggregated to each pixel in proportion to the DN value of the nighttime light images (Ghosh et al., 2010a; 2010b; Oda and Maksyutov, 2011; Zhao et al., 2012). Where people live, however, is not necessarily consistent with where wealth is produced, and this inconsistency will generate some spatial errors when nighttime light image data are used to disaggregate GDP. Chen and Nordhaus (2010) found some errors emerged but still believed that "luminosity has informational value for countries with low-quality statistical systems" when they used a methodology similar to this one to estimate and disaggregate GDP. Furthermore, in this study I mainly analyzed relative changes of GDP between two years. In most cases the increases in brightness and area of nighttime lights reflect the local economy's growth and I therefore believe this approach is valuable and the errors are acceptable.

Two shortcomings remain where GDP is spatially disaggregated to the pixel level in proportion to the DN value of the nighttime light imagery. First, a basic logic of the spatial disaggregation is that a region with a more developed economy usually produces a larger GDP and has brighter lights at night. For regions with the same economic development level, regions with larger populations should have a larger GDP. Admittedly, brightness of nighttime lights also reflects population information. Regions with brighter lights at night usually have larger populations (Sutton et al., 1997; Sutton et al., 2001). However, regions with the same brightness of nighttime lights should always have relatively small differences in population which lead to relatively small variations in GDP. Thus, following the previous approach in which only brightness of nighttime lights is used as a measure of GDP, regions in each province with the same DN value on a nighttime light image would be attributed to the same amount of GDP and so do not show variation in productivity caused by differences in population. More importantly, a certain number of saturated pixels exist in stable light image composites. The saturated pixels have values of 63 but their actual DN values should be larger than 63 (Doll, 2008). Urban core regions with the saturated pixels would have underestimated GDP.

To overcome the above two drawbacks, I jointly used the nighttime light images and the LandScan population data to disaggregate GDP. Due to different population counts, regions with the same DN value in a nighttime light image were allocated different amounts of GDP in the disaggregation process. Figure 3.2 shows that average population density derived from the LandScan population data has an exponential relationship with nighttime light DN value. When the nighttime light DN value is relatively small, the population density increases slowly. However, rapid increases in population density at increasingly higher DN values leads to an exceptionally large population density in urban core regions with DN values of 63. Thus the relatively large population compensates for under-distribution of GDP generated by the under-valued nighttime light image data (i.e. the saturated pixels) in urban core areas.

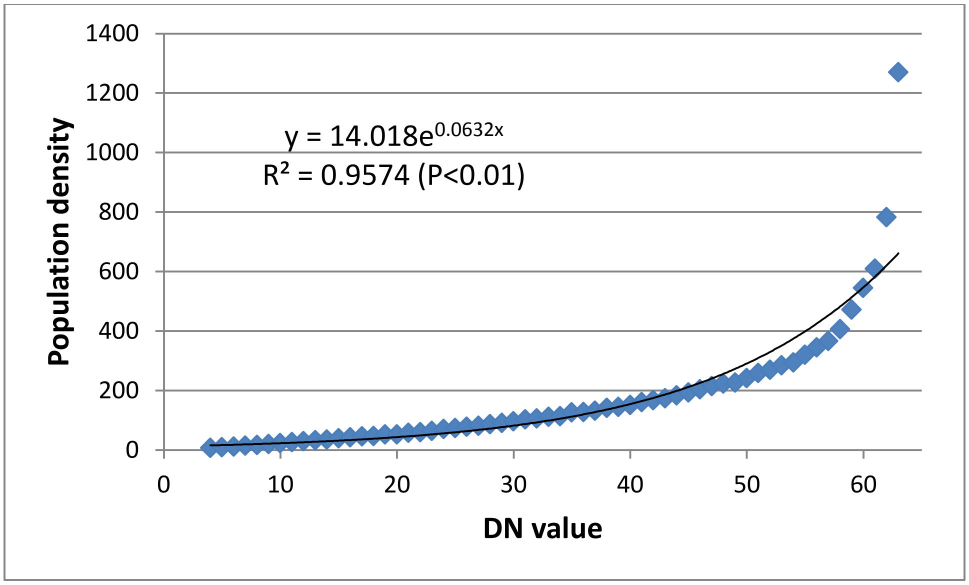

Figure 3.2. The correlation between DN value of 2001 stable lights imagery and population density.

In this study, I used the LandScan population dataset of 2008 to disaggregate official GDP data of 2001 and 2007. The temporal inconsistency of the LandScan population data with the official GDP data seems to generate some errors. However, Zhao et al. (2012) have found that the errors are actually very small because the use of nighttime light images that are temporally consistent with the official GDP data reduces the errors generated by a single-year of population data. I did not use early versions of the LandScan population dataset that are temporally consistent with the official GDP data because the Oak Ridge National Laboratory (2010b) does not release and recommend use of the earlier versions of the LandScan population dataset. Data and algorithms used to establish the LandScan population dataset are updated every year, so more errors exist in the earlier versions.

The nighttime light images of 2001 and 2007 were multiplied by the LandScan population dataset to produce nighttime-light-population images of 2001 and 2007 respectively. The Chinese boundary vector layer was overlaid on the nighttime-light-population images to obtain each province's sum light-population. Light-population does not correspond to any measurement unit in our real life, representing neither people count nor luminance of nighttime lights. It indicates economically-weighed-population because in this study brightness of nighttime lights is used as a measure of economic level. In other words, if two regions have the same population but different brightness of nighttime lights, the region with brighter nighttime lights has larger light-population than the one with dimmer nighttime lights. A province's sum light-population is equal to the sum of the DN values of all the pixels on a nighttime-light-population image in the province. The amount of GDP represented by one unit of light-population was symbolized by *U* and computed by equation 3:

$$U = \frac{GDP}{SLP} \qquad (3)$$

where *SLP* is a province's sum light-population.

The Chinese boundary vector layer was then converted to two raster maps for 2001 and 2007. In each of the raster maps, one province had a uniform DN value which is the amount of GDP indicated by one unit of light-population. GDP maps for 2001 and 2007 were produced by multiplying the nighttime-light-population images for those years with their corresponding raster maps converted from the Chinese boundary vector layer. A map showing spatio-temporal changes in GDP (Figure 3.3) was produced by subtracting the GDP map of 2001 from that of 2007.

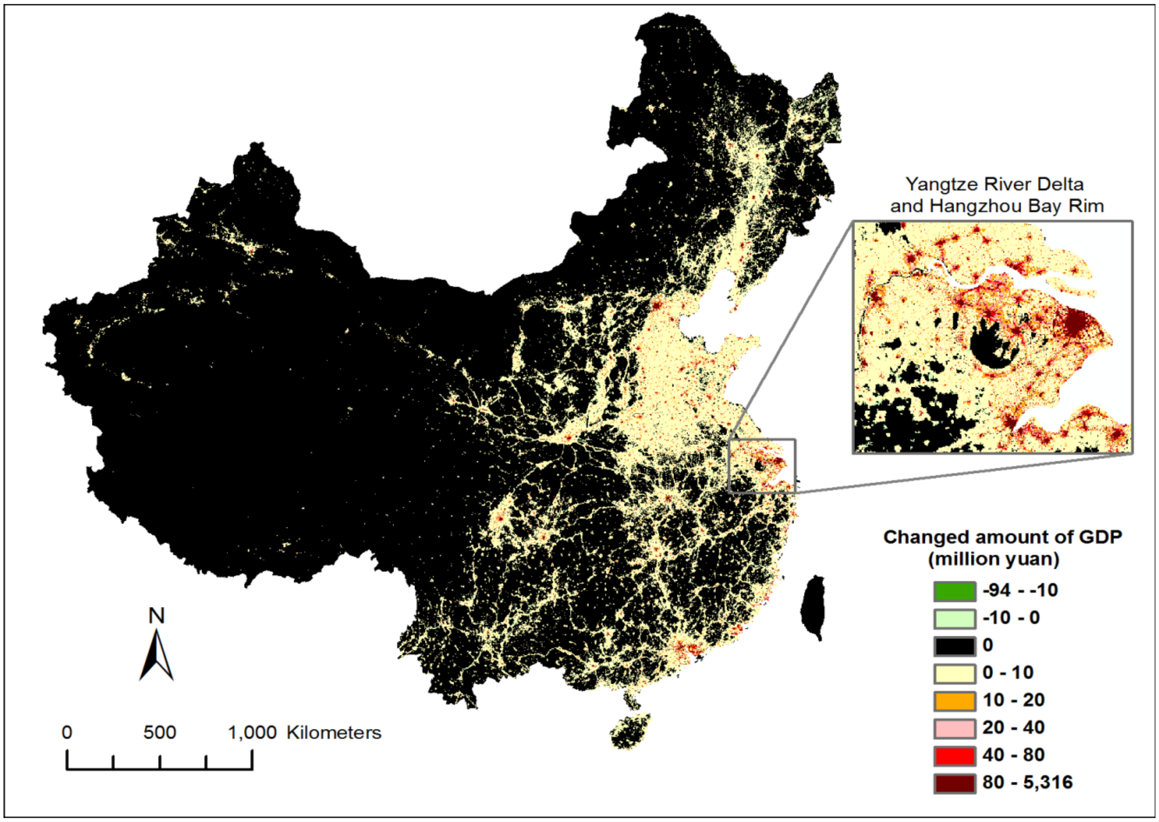

Figure 3.3. GDP spatio-temporal change from 2001 to 2007 with data for Hong Kong, Macao, and Taiwan excluded (GDP in million Yuan).

Mapping NPP changes

The DN values of the improved MODIS annual NPP images were converted to the amounts of annual NPP for individual pixel areas (t C/km^2/yr) based on equation 4:

$$DN_{NPP} = \begin{cases} DN * F, & DN \neq 65535 \\ 0.0, & DN = 65535 \end{cases} \qquad (4)$$

where F is a scale factor (0.1) specific to the improved MODIS GPP/NPP image products (Zhao, 2010). A map showing spatio-temporal changes in NPP (Figure 3.4) was produced by subtracting NPP in 2001 from NPP in 2007.

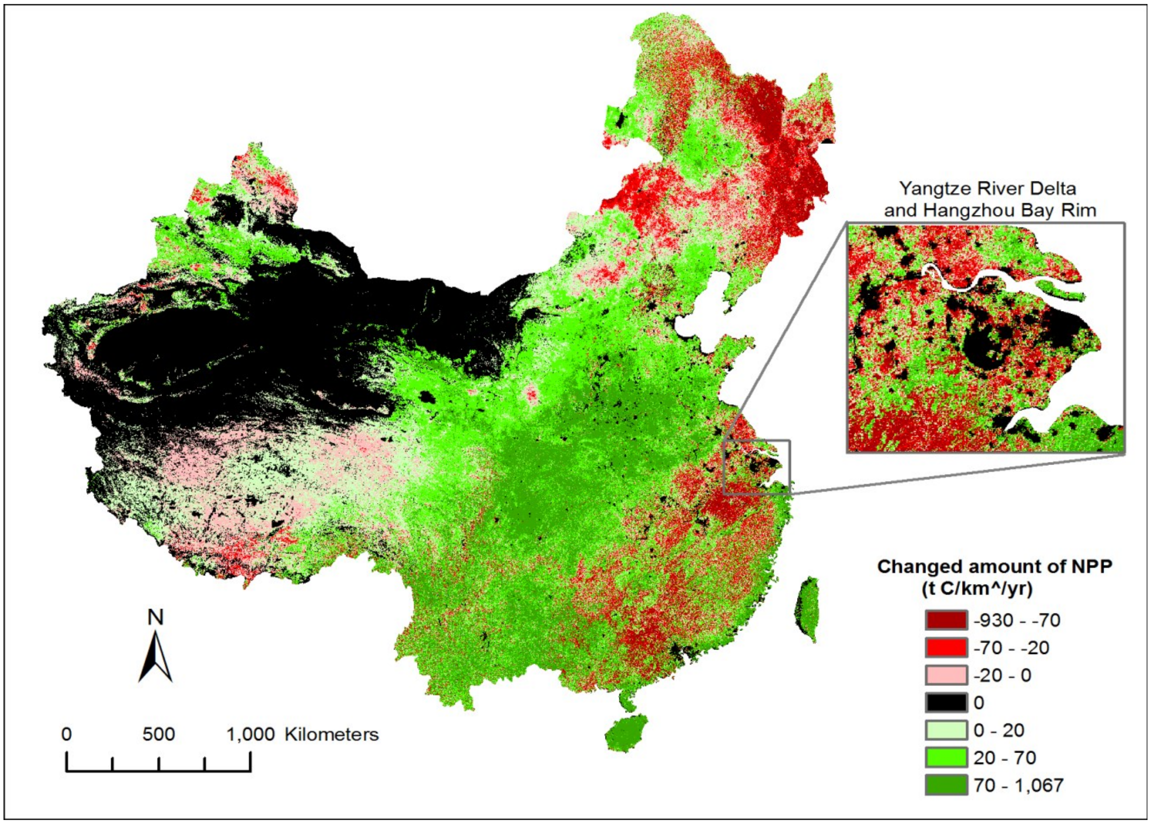

Figure 3.4. NPP spatio-temporal change from 2001 to 2007 (NPP in t C/km^2/yr).

Integrating GDP and NPP changes

To minimize impacts of noise and random errors in the nighttime light image data and the MODIS annual NPP image data, I needed to define a threshold below which minor GDP and NPP changes were not considered significant and consequently not treated as changes. I set the threshold at 5% of the overall changes since there is no statistical method of determining an optimal threshold. An integrated map (Figure 3.5) that shows the changes of GDP and NPP simultaneously was produced based on equation 5:

$$DN_{IN} = \begin{cases} 1, & DN_{NPP'} > 0 \text{ and } DN_{GDP'} = 0 \\ 2, & DN_{NPP'} < 0 \text{ and } DN_{GDP'} = 0 \\ 3, & DN_{NPP'} = 0 \text{ and } DN_{GDP'} > 0 \\ 4, & DN_{NPP'} = 0 \text{ and } DN_{GDP'} < 0 \\ 5, & DN_{NPP'} > 0 \text{ and } DN_{GDP'} < 0 \\ 6, & DN_{NPP'} < 0 \text{ and } DN_{GDP'} > 0 \\ 7, & DN_{NPP'} > 0 \text{ and } DN_{GDP'} > 0 \\ 8, & DN_{NPP'} < 0 \text{ and } DN_{GDP'} < 0 \\ 9, & DN_{NPP'} = 0 \text{ and } DN_{GDP'} = 0 \end{cases} \tag{5}$$

where DN_{IN} is the DN value of the integrated map, $DN_{NPP'}$ is the DN value of the spatio-temporal NPP change map, and $DN_{GDP'}$ is the DN value of the spatio-temporal GDP change map.

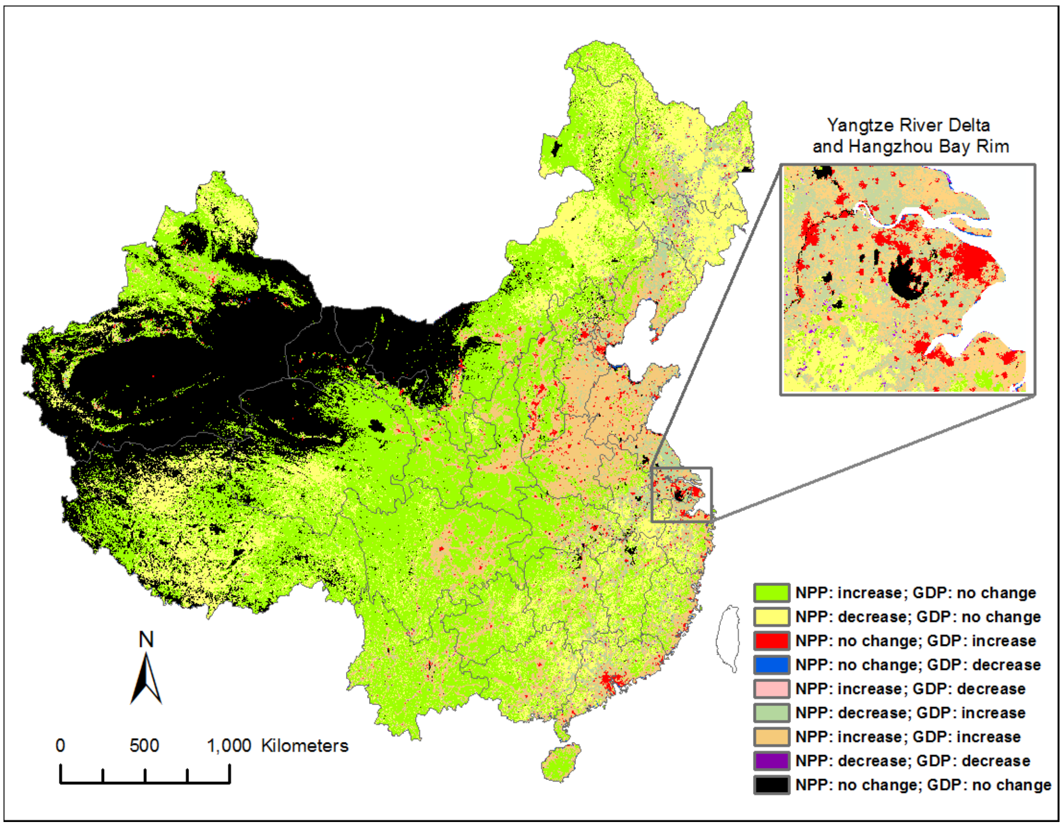

Figure 3.5. Integrated NPP and GDP change from 2001 to 2007 with data for Hong Kong, Macao, and Taiwan excluded.

Reclassifying land cover type products

The images of the MODIS Land Cover Type 4 were reclassified based on equation 6:

$$DN_{re} = \begin{cases} 0, \ \ DN_{lct} = 0 \\ 1, \ \ DN_{lct} = 1, or\ 2, or\ 3, or\ 4, or\ 5 \\ 2, \ DN_{lct} = 6 \\ 3, \ DN_{lct} = 7 \\ 4, \ DN_{lct} = 8 \end{cases} \tag{6}$$

where DN_{re} is the DN value of the reclassified land cover images, and DN_{lct} is the DN value of the Land Cover Type 4 images. Original Land Cover Type 4 images include nine land cover types that are water (DN value=0), evergreen needleleaf vegetation (DN value=1), evergreen broadleaf vegetation (DN value=2), deciduous needleleaf vegetation (DN value=3), deciduous broadleaf vegetation (DN value=4), annual broadleaf vegetation (DN value=5), annual grass vegetation (DN value=6), non-vegetated land (DN value=7), and urban (DN value=8). The reclassified land cover images contain five land cover types: water (DN value=0), forest (DN value=1), grass (DN value=2), barren land (DN value=3), and urban (DN value=4). The Land Cover Type 4 (NPP-based) classification scheme of the MCD12Q1 does not have separate classes for shrubs and crops. After the reclassification some shrubs and crops (mainly derived from the original class of *annual broadleaf vegetation*) are incorporated into the forest class. To reduce uncertainties and errors caused by the reclassification, I further combine the classes of forest and grass into vegetated land. In the following analyses of land cover change and the impacts of land cover change on ecosystem production I will pay particular attention to vegetated land even though changes to the areal extent of forestland and grassland will still be exhibited. The areas of each reclassified land cover type are calculated for 2001 and 2007 for additional analyses of the impacts of China's economic growth on its ecosystems' production.

Detecting land cover changes

Economic growth often leads to urban expansion and consequently land-cover conversion, which can affect ecosystem production (Milesi et al., 2003). Thus, post-classification change detection was performed using reclassified MODIS land cover type images. A change detection matrix (Table 3.1) with basic elements of forest, grass, barren land, and built-up area was produced. A major land cover type, water, was excluded from the change detection matrix because nearly no land-cover changes related to water body from 2001 to 2007. The expected outcomes of co-development are that as economic growth occurs, forest and grasslands should be protected, so the area of forestland and/or grassland should not be reduced. Regions experiencing land-cover conversions are shown in Figure 3.6. These methods are used to test the fourth hypothesis proposed in this dissertation.

Table 3.1. The change detection matrix with basic elements of land cover. The values in individual cells represent changes in area (km^2).

	To 2007					
		Forest	Grass	Soil	Built-up	Total area in 2001
From	Forest	2,366,736	1,152,003	54,701	92	3,573,449
	Grass	483,075	2,664,894	109,855	11	3,257,826
2001	Soil	80,945	193,449	2,169,732	0	2,444,126
	Built-up	650	1,438	49	79,091	81,228
	Total area in 2007	2,931,406	4,011,785	2,334,337	79,101	

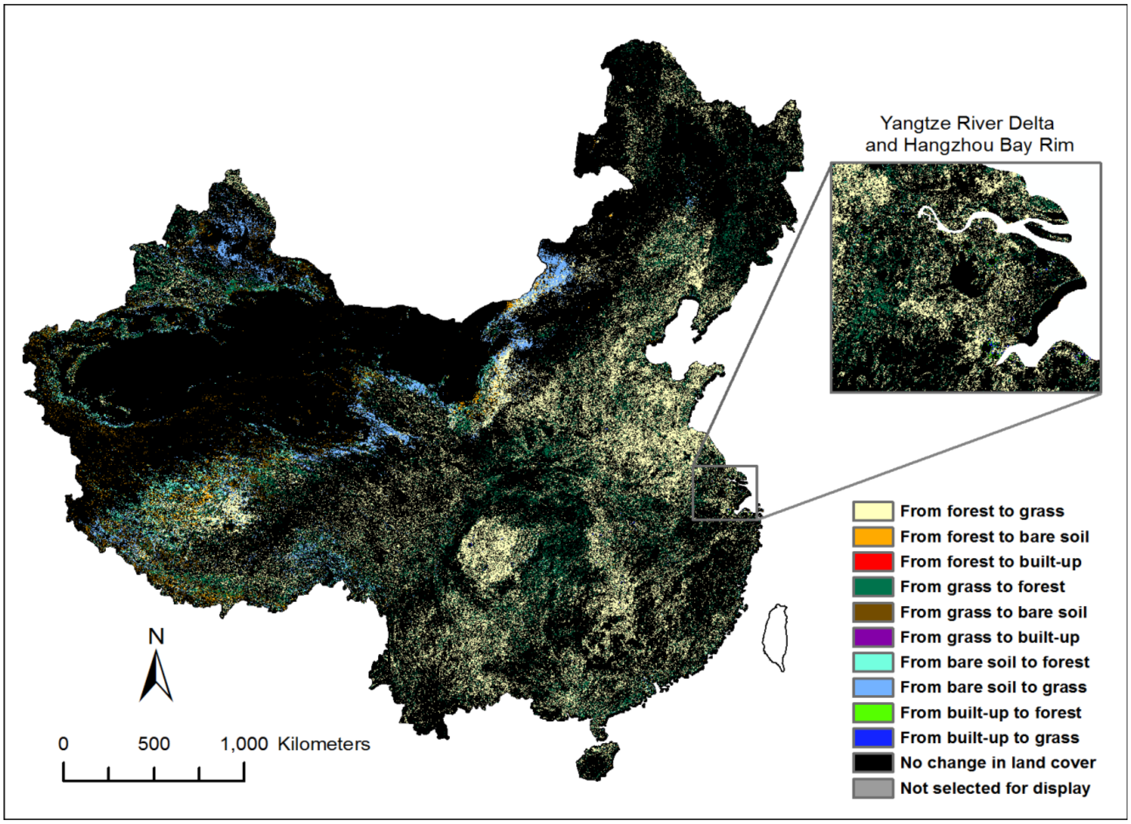

Figure 3.6. Land cover change detection with data for Taiwan excluded.

Delimiting developed and undeveloped areal extents

Natural factors (e.g. climate variability and change) can lead to large-scale changes in NPP (Chen et al., 2006; Zhao and Running, 2010), but in developed areas anthropogenic activities are dominant factors affecting changes in NPP. For example, humans convert woodland, grassland, and farmland into built-up land which results in decreasing NPP despite climate warming, nitrogen deposition, or increases in precipitation that would otherwise lead to NPP increases. Similarly, economic growth may increase demand for a healthier urban environment, leading to an increase in urban green space. The addition of urban green space will lead to increased NPP in urban areas even though natural factors may tend to reduce ecosystem production.

To safely assume that the surveyed changes of NPP are mainly affected by anthropogenic factors and not natural forces, developed areas need to be separated from undeveloped areas. Since ephemeral lights have been removed from the stable light images, I assume that the brightly lit areas (with non-zero DN values in the nighttime light images) correspond to the developed areas, and the undeveloped areas were not brightly lit (with DN value of 0 in the nighttime light images). Developed areas delimited by lit areas are larger than actual developed areas because of the blooming effects, a phenomenon where urban peripheries are brightened by urban lights (Imhoff et al., 1997b). In previous studies, DN threshold values in nighttime light images were usually used to eliminate the effects of blooming (Imhoff et al., 1997b; Liu et al., 2012; Small et al., 2005). Yet, different cities have different thresholds in nighttime light images that are appropriate for delimiting urban extents (Liu et al., 2012; Small et al., 2005). Thus, it is impractical to find out every city's thresholds and use the thresholds to delimit urban extents across the entire Chinese territory. But, based on high resolution Google Map data, I found most such urban periphery regions are croplands. Although the urban periphery regions brightened by urban lights are not actual developed areas, GDP is produced in these regions and ecosystem production in these regions is greatly affected by socioeconomic activities. Hence, in this study I did not use the previous threshold method to remove brightened urban periphery regions from the developed areas.

From 2001 to 2007 China experienced not only tremendous economic growth but also large urban sprawl. In the process of urban sprawl, land cover types have been changed and newly developed areas have emerged. To explore whether decreases in NPP accompany the urban sprawl, newly developed and established developed areas need to be differentiated and their extents need to be delimited. This is accomplished by classifying areas with non-zero DN value in the 2001 nighttime light image as established developed areas and classifying areas with a zero DN value in the 2001 nighttime light image and non-zero DN value in the 2007 nighttime light image as newly developed areas. In addition, I categorize the undeveloped areas within a 5 kilometer buffer of developed areas for the purpose of comparing NPP in developed areas to their adjacent undeveloped areas. This categorization and comparison facilitates assessment of the extent to which natural forces generated uneven impacts on ecosystem production between developed and undeveloped areas.

Province level changes

The IPAT equation suggests that significant negative relationships should exist between economic growth and environmental impacts, and so as GDP increases, NPP should theoretically decrease (Imhoof et al., 2004). Yet, according to co-development policy, most developed areas should experience increases in GDP and NPP simultaneously (Geng, 2011). To explore the relationships between economic development and ecosystem production at the province level, I determine the total GDP and NPP changes in all established developed and newly developed areas in each province. I then perform correlation analysis of the total changes and the percentage changes in GDP and NPP in developed areas. Additionally, the areal extent of regions with increases in both GDP and NPP and the areal extent of regions with increases in GDP and decreases in NPP are calculated in order to cope with possible situations where there are no significant correlations. These methods are used to test the second hypothesis proposed in this dissertation.

City level changes

The modifiable areal unit problem (MAUP) can affect results of statistical tests when the results obtained at a spatial scale are applied to a different spatial scale (Openshaw, 1984). To test whether the changing patterns of GDP, NPP, and land cover are consistent across different geographic scales and, more importantly, to verify the existence of impacts of economic growth on ecosystem production at a finer spatial scale, I select ten cities, each a provincial capital, for additional analysis. Specifically, five of the cities (Hohhot, Lanzhou, Urumqi, Xining, and Yinchuan) were selected from the western and northern regions of China where the economies were once the least developed. The other five cities (Fuzhou, Guangzhou, Hangzhou, Jinan, and Nanjing) were selected from the eastern coastal region where the economies were the most developed. The GDP and NPP for each city were obtained by aggregating GDP and NPP of each pixel in the boundary of the city. Correlation analyses were conducted again to test the relationships between total changes and percentage changes of GDP and NPP for the ten cities. These methods are used to test the second hypothesis proposed in this dissertation. Comparison of NPP changes between developed areas and the undeveloped areas within a five kilometer buffer of the developed areas was conducted at the city level to test the third hypothesis proposed in this dissertation that anthropogenic activities in developed areas generated unique impacts on ecosystem production.

IV. RESULTS

NPP trends in developed and undeveloped areas

Established developed areas are those areas that were developed in 2001 and 2007. Newly developed areas are those areas that were undeveloped in 2001 and developed in 2007. Undeveloped areas, in this case, are those areas that lack any development as measured by nighttime lights imagery and that are within a 5 kilometer buffer of developed areas. The trends in these three areas are compared across China to establish that NPP in developed areas and their adjacent undeveloped areas are equally effected by natural factors—that differences in natural factors do not account for differences in NPP between neighboring areas. Hence, differences in NPP should be attributable to human influence in established developed, newly developed, and undeveloped areas.

Figure 4.1 shows that annual variations in NPP among established developed, newly developed, and undeveloped areas follow similar upward and downward trends: (1) the smallest and the largest NPP amounts are in 2001 and 2004 respectively; (2) NPP in 2007 is larger than that in 2001 but smaller than in 2004; and (3) in 2005 NPP precipitously decreases. The general patterns of increase from 2001 to 2004 and decrease from 2004 to 2007 are the same for established developed, newly developed, and undeveloped areas, which implies that natural forces produced the same outcomes on ecosystem production in all three regions. Moreover, it is especially important to note that the slopes of the newly developed and undeveloped (5 km buffer) lines are nearly the same in 2001 and 2002 (i.e., the difference in slope is 0.008) (Figure 4.1). Newly developed areas were completely undeveloped in 2001 and were not completely developed until 2007, so only a small portion of the newly developed areas were actually developed in 2002. (The rest would be developed in the following years.) In 2001 and 2002 ecosystem production in newly developed and undeveloped areas was predominantly influenced by natural forces and the matching slopes demonstrate this matching influence of natural forces on developed and undeveloped areas.

However, as increasingly more land in newly developed areas was developed, human factors increasingly influenced NPP changes in newly developed areas. After 2002 the slopes of the developed area lines diverge from the slope of the undeveloped line (Figure 4.1). Additionally, the established developed area line fluctuates value more than the newly developed and undeveloped lines (Figure 4.1). Figure 4.2 exhibits that small differences exist in the percentage change of NPP between established developed, newly developed, and undeveloped areas. Anthropogenic activities are more concentrated in established developed areas than in newly developed and undeveloped areas. Hence, anthropogenic activities contribute to the differences in these percentage changes. In the following sections, I will discuss whether the anthropogenic activities produced positive or negative impacts on ecosystem production by analyzing the percentage changes of NPP.

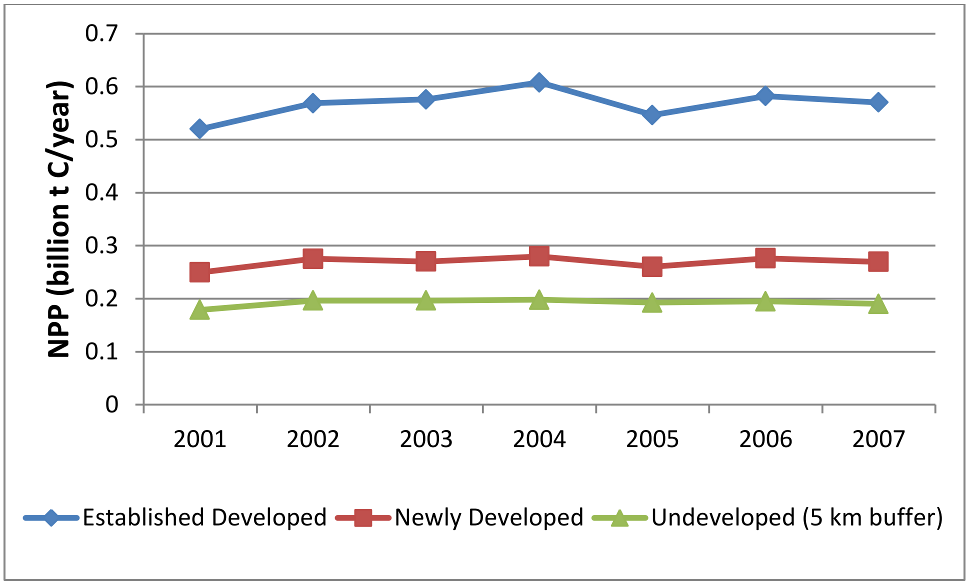

Figure 4.1. Time-series of total NPP in established developed, newly developed, and undeveloped (5 km buffer) areas.

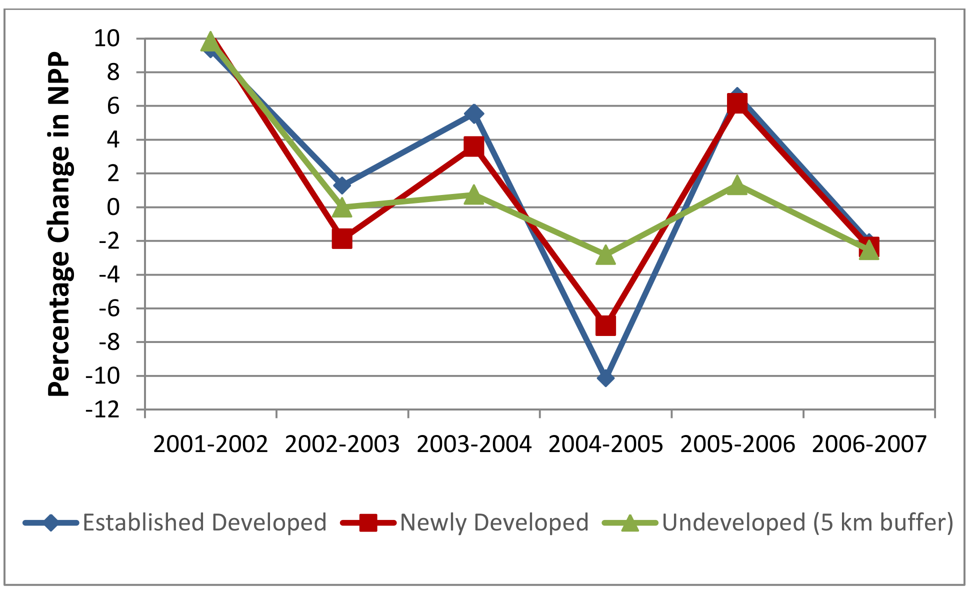

Figure 4.2. NPP percentage changes in established developed, newly developed, and undeveloped (5 km buffer) areas.

Changing patterns of GDP and NPP at different geographic scales

National level changes

From 2001 to 2007, China's total GDP increased from 10,676.62 billion Yuan (1,713.74 billion 2013 US dollars) to 27,562.46 billion Yuan, an increase of 158.16%. During this period China's developed areas increased by 449,675 km^2. In 2007, 657.95 billion Yuan GDP (2.39% to the total GDP in 2007) was produced in newly developed areas. In established developed areas GDP increased 16,227.89 billion Yuan, an increase of 151.99%.

From 2001 to 2007, China's total NPP increased from 2.56 billion t C/year to 2.74 billion t C/year, an increase of 6.92%. In established developed areas, NPP increased from 0.52 billion t C/year to 0.57 billion t C/year, an increase of 9.36%. In newly developed areas NPP increased from 0.25 billion t C/year to 0.27 billion t C/year, an increase of 7.88%. Therefore, at the national scale, China experienced coupled increases in GDP and NPP in developed areas.

Province level changes

From 2001 to 2007, all Chinese provinces experienced increases in GDP. Guangdong had the largest increase of 2043.67 billion Yuan and Tibet had the smallest increase of 20.35 billion Yuan (Table 4.1). Inner Mongolia had the largest percentage increase in GDP increase – a threefold increase. Hubei had the smallest percentage of GDP increase, but still doubles from 2001 to 2007 (Table 4.1).

Table 4.1. Changes in GDP for 31 provinces. GDP percentage changes = (GDP_{2007}-GDP_{2001})/GDP_{2001}×100%.

Province	GDP (billion Yuan)		Total GDP changes (billion Yuan)	GDP (% change)	Lit area (km^2)	
	In 2001	In 2007			In 2001	In 2007
Anhui	329.01	736.42	407.41	123.83	51389	84636
Beijing	284.57	935.33	650.77	228.69	12005	11729
Chongqing	174.98	412.25	237.27	135.60	12986	25714
Fujian	425.37	924.91	499.55	117.44	40298	49652
Gansu	107.25	270.24	162.99	151.97	24427	36160
Guangdong	1064.77	3108.44	2043.67	191.94	81187	101431
Guangxi	223.12	595.57	372.45	166.93	45429	61931
Guizhou	108.49	274.19	165.70	152.73	18028	33448
Hainan	54.60	122.33	67.73	124.06	11266	14067
Hebei	557.78	1370.95	813.17	145.79	107595	114600
Heilongjiang	356.10	706.50	350.40	98.40	71915	101796
Henan	564.01	1501.25	937.24	166.17	106415	131807
Hubei	466.23	923.07	456.84	97.99	43436	69027
Hunan	398.30	920.00	521.70	130.98	34973	63222
Inner Mongolia	154.58	609.11	454.53	294.05	35428	63806
Jiangsu	951.19	2574.12	1622.92	170.62	87069	98037
Jiangxi	217.57	550.03	332.46	152.81	24466	44609
Jilin	203.25	528.47	325.22	160.01	43067	58522
Liaoning	503.31	1102.35	599.04	119.02	74296	93029
Ningxia	29.84	88.92	59.08	198.01	9808	13997
Qinghai	30.10	78.36	48.27	160.38	5879	9819
Shaanxi	184.43	546.58	362.15	196.37	43280	62409
Shandong	943.83	2596.59	1652.76	175.11	146621	152301
Shanghai	495.08	1218.89	723.80	146.20	6043	6043
Shanxi	178.00	573.34	395.34	222.10	63401	70586
Sichuan	442.18	1050.53	608.35	137.58	38258	74750
Tianjin	184.01	505.04	321.03	174.46	12203	12212
Tibet	13.87	34.22	20.35	146.66	1372	2970
Xinjiang	148.55	352.32	203.77	137.17	28534	53052
Yunnan	207.47	474.13	266.66	128.53	37210	71014
Zhejiang	674.82	1878.04	1203.23	178.31	50138	58982
Sum	10676.63	27562.46	16885.84	158.16	1368422	1845358

During the same period, most provinces experienced increases in NPP except Beijing, Jilin, Heilongjiang, Jiangxi, and Guangdong. In established developed areas only

Heilongjiang, Jilin, and Tibet experienced decreases in NPP, and in newly developed areas only Beijing, Guangdong, Heilongjiang, Jilin, and Tibet experienced decreases in NPP (Table 4.2). Therefore, at the province scale 26 of 31 Chinese provinces experienced coupled increases in GDP and NPP in their established and newly developed areas.

However, Pearson correlation coefficients indicate that at the province level the total changes in NPP in developed areas are not significantly related to the total changes in GDP (r=0.262, p=0.154). Additionally, no significant relationship exists between percentage changes in NPP and GDP in developed areas (r=0.229, p=0.215). Figures 4.3 and 4.4 show that changes in NPP are not proportional to the changes in GDP at the province level. Some provinces, particularly western and central provinces (e.g. Henan, Sichuan, and Yunnan), experienced relatively large increases in the amount of NPP but relatively small increases in the amount of GDP, whereas some provinces, particularly eastern provinces (e.g. Guangdong, Jiangsu, and Zhejiang) experienced relatively large increases in the amount of GDP but relatively small increases in the amount of NPP (Figure 4.3). Thus, quantitative relationships between total changes (or percentage changes) in GDP and NPP cannot be found in Figure 4.3 or 4.4.

City level changes

The 10 selected cities all experienced large increases in GDP (Table 4.3). The average percentage of GDP increase for the ten cities is 148.19%, slightly smaller than that of the 31 provinces (158.16%). Only 2 of the 10 cities (Hangzhou and Nanjing) experienced decreases in overall NPP, and these two cities also had decreased NPP in their established developed areas (Table 4.3). In newly developed areas besides

Hangzhou and Nanjing, Guangzhou experienced decrease in NPP (Table 4.3). Hence, at the city scale eight of the ten cities experienced coupled increases in GDP and NPP in their established developed areas, and seven of the ten cities experienced coupled increases in GDP and NPP in their newly developed areas.

However, no significant correlations can be found between total changes in NPP and GDP (r=0.215, P=0.552) or between percentage changes in NPP and GDP (r=0.338, P=0.340) in developed areas at the city level. Figures 4.5 and 4.6 show changing patterns of GDP and NPP at the city level. Fuzhou and Jinan have relatively large increases in NPP and relatively small increases in GDP. Guangzhou has relatively large increases in GDP and relatively small increase in NPP. Lanzhou, Urumqi, Yinchuan, Hohhot, and Xining have medium increases in GDP and NPP. Nanjing and Hangzhou have relatively large increases in GDP but experienced decreases in NPP. Consequently, no quantitative correlations can be found between changes of GDP and NPP.

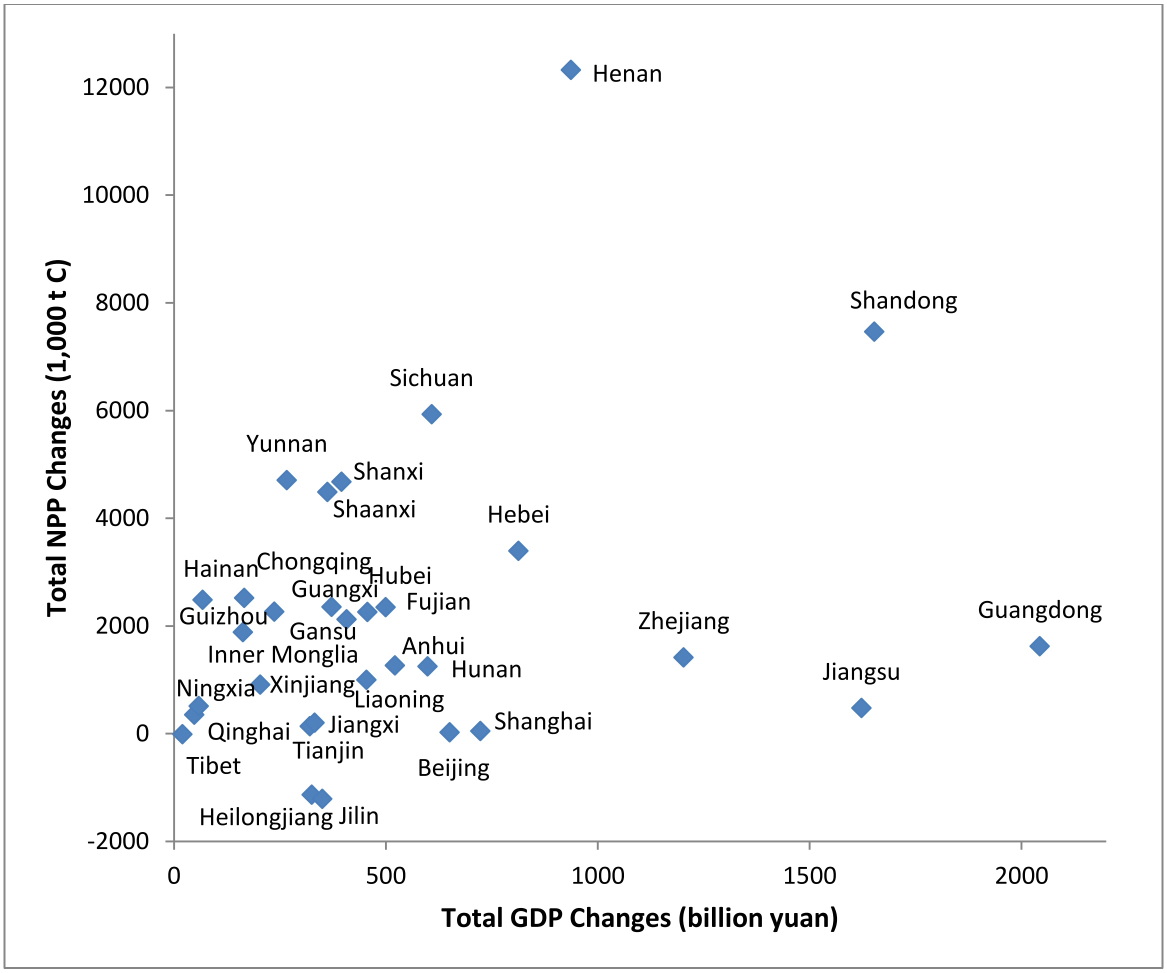

Figure 4.3. Bivariate scatter plot of the amounts GDP and NPP changes in the developed areas of 31 provinces.

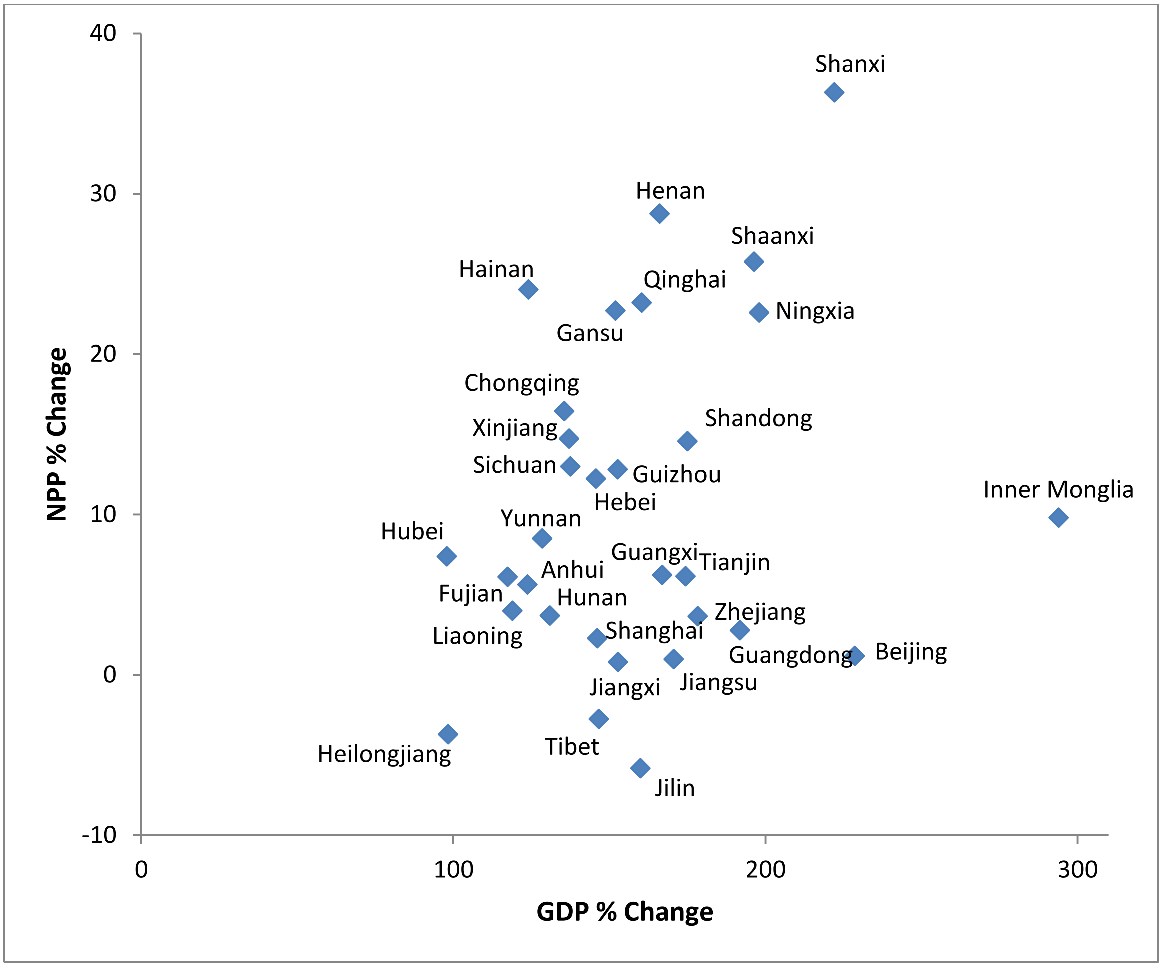

Figure 4.4. Bivariate scatter plot of the percentage changes in GDP and NPP in the developed areas of 31 provinces.

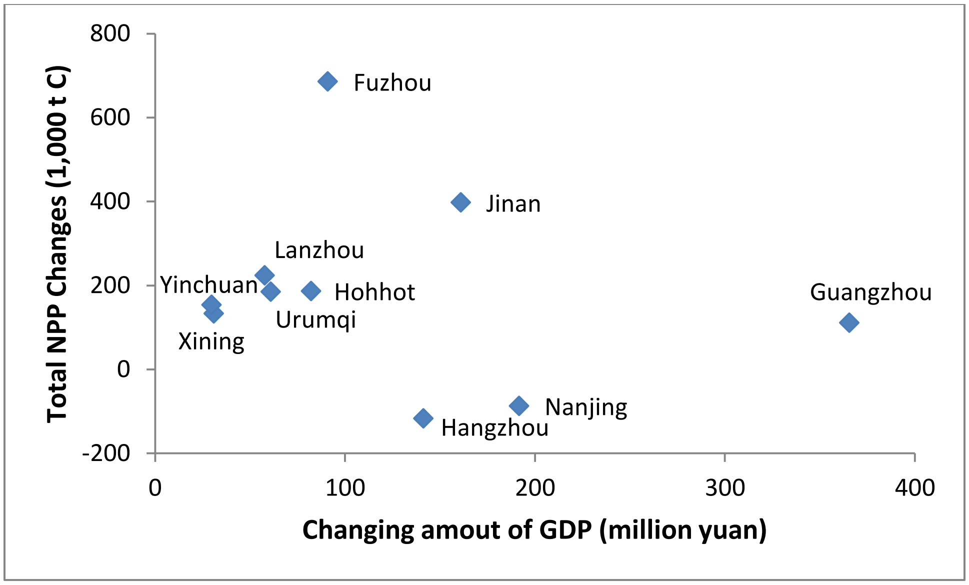

Figure 4.5. Bivariate scatter plot of the amount of GDP and NPP changes in the developed areas of 10 cities.

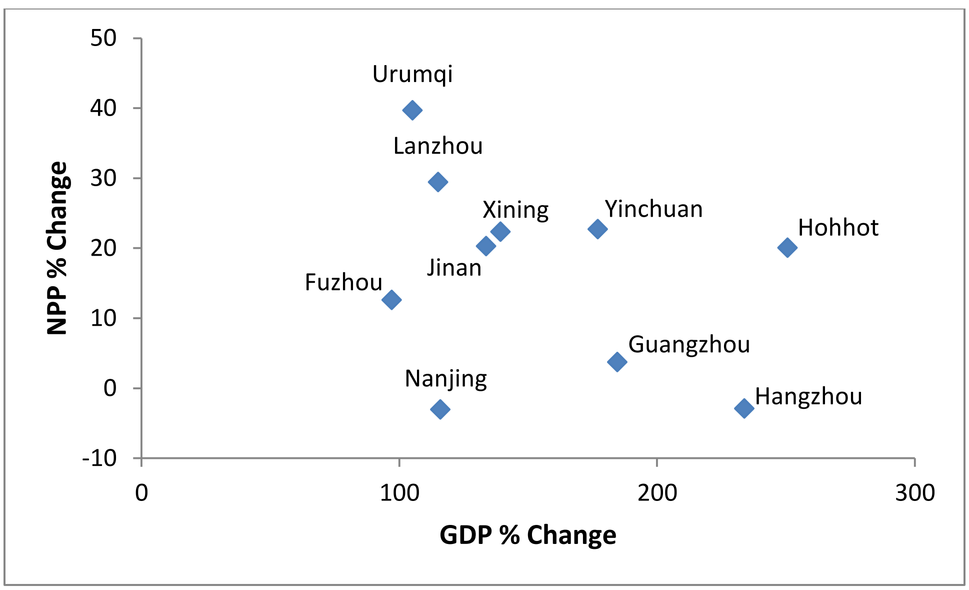

Figure 4.6. Bivariate scatter plot of the percentage changes in GDP and NPP in the developed areas of 10 cities.

Pixel level changes

At the pixel level, coupled increases in NPP and GDP (12.89% of the total number of pixels in China) cover an area approximately three times larger than those with increases in GDP and decreases in NPP (3.99% of the total number of pixels in China). More specifically, established developed areas (Figure 3.5) had over 830,638 km^2 of coupled increases in both NPP and GDP, whereas only 247,493 km^2 had increases in GDP and decreases in NPP. In newly developed areas, 376,617 km^2 had coupled increases in NPP and GDP while only 126,674 km^2 had increases in GDP and decreases in NPP. Across China only a few scattered pixels had small decreases in GDP accompanied by either decreases (0.31% to total area), increases (0.66% to total area), or no change (0.14% to total area) in NPP (Table 4.4). The above values reveal that at the pixel level 64.11% of established and 70.21% of newly developed areas experienced coupled increases in NPP and GDP during 2001 to 2007. Significant relationships between total changes in NPP and GDP (r=0.207, p=0.438) or between percentage changes in NPP and GDP in developed areas (r=0.185, p=0.537) are not found, however, at the pixel level.

Therefore, across different geographic levels (national, province, city, and pixel levels), most Chinese developed areas have experienced coupled increases in NPP and GDP but there is no significant quantitative relationship between the increases of NPP and GDP. Opposite to what the IPAT theory suggests (that economic growth produces negative impacts on ecosystem production (Rees, 1992)), large areas of NPP decrease did not accompany increases in GDP. Moreover, whereas the IPAT theory asserts that solid correlations exist between economic growth and environmental impacts (Hubacek et al., 2007), no significant relationship can be found between changes of GDP and NPP at either the province, the city, or the pixel level.

Table 4.2. Changes in NPP for 31 provinces. NPP percentage changes = $(NPP_{2007}-NPP_{2001})/NPP_{2001}\times100\%$. (There are no undeveloped and newly developed areas in Shanghai).

Province	Total NPP (million t C)		NPP (Percent change)			
	In 2001	In 2007	Whole areas	Undeveloped areas	Established developed areas	Newly developed areas
Anhui	67.66	68.34	1.01	-4.81	5.23	6.16
Beijing	2.64	2.58	-1.97	-13.11	1.38	-5.53
Chongqing	45.36	52.96	16.75	16.89	16.30	16.55
Fujian	96.56	99.78	3.33	1.50	6.68	4.49
Gansu	64.09	77.75	21.32	21.11	22.76	22.62
Guangdong	119.05	118.51	-0.45	-3.59	4.23	-0.84
Guangxi	164.46	169.84	3.27	2.39	7.38	4.12
Guizhou	110.57	120.98	9.42	8.69	13.54	12.10
Hainan	27.78	34.75	25.08	25.71	24.03	23.98
Hebei	43.37	48.34	11.48	10.15	11.91	16.15
Heilongjiang	143.00	126.12	-11.80	-14.20	-3.54	-4.00
Henan	54.05	69.94	29.39	31.83	29.56	26.04
Hubei	84.61	94.20	11.34	13.59	7.53	7.17
Hunan	126.53	128.73	1.74	1.01	3.95	3.39
Inner Mongolia	139.78	144.76	3.56	3.07	8.93	10.72
Jiangsu	49.96	50.50	1.08	4.25	0.54	4.49
Jiangxi	108.53	107.67	-0.79	-1.26	0.62	0.95
Jilin	63.82	55.96	-12.32	-15.46	-5.43	-6.63
Liaoning	50.31	52.00	3.35	2.31	4.20	3.32
Ningxia	7.10	8.89	25.12	26.29	19.29	31.11
Qinghai	52.27	59.80	14.40	14.14	23.37	22.98
Shaanxi	54.89	72.06	31.29	33.86	24.28	29.57
Shandong	52.91	60.74	14.79	22.43	14.19	20.68

Table 4.2 Continued. Changes in NPP for 31 provinces. NPP percentage changes = $(NPP_{2007}-NPP_{2001})/NPP_{2001}\times100\%$. (There are no undeveloped and newly developed areas in Shanghai).

Province	Total NPP (million t C)		NPP (Percent change)			
	In 2001	In 2007	Whole areas	Undeveloped areas	Established developed areas	Newly developed areas
Shanghai	2.07	2.11	2.27	No data	2.27	No data
Shanxi	28.16	38.60	37.10	37.77	35.70	39.30
Sichuan	257.02	287.14	11.72	11.45	13.17	12.80
Tianjin	2.19	2.32	6.14	5.25	6.13	10.24
Tibet	69.88	74.57	6.71	6.78	-3.59	-2.22
Xinjiang	66.76	73.71	10.42	9.98	15.73	13.91
Yunnan	337.98	366.85	8.54	8.55	8.93	8.11
Zhejiang	71.56	71.92	0.51	3.20	4.34	0.97
Sum	2016.55	2153.05	6.77	6.09	9.36	7.88

Table 4.3. Changes in GDP and NPP for 10 selected cities.

City	GDP		Total NPP		NPP in established developed areas		NPP in new developed areas		NPP in undeveloped areas	
	Total change (billion yuan)	Percentage change	Total change (t C)	Percentage change	Total change (t C)	Percentage change	Total change (t C)	Percentage change	Total change (t C)	Percentage change
Fuzhou	91.02	0.97	877972	10.15	581598	13.01	103968	10.76	192406	5.99
Guangzhou	365.51	1.85	86410	2.55	114255	4.22	-3729	-1.48	-24116	-5.70
Hangzhou	141.24	2.34	-355990	-5.57	-66556	-2.03	-50593	-6.89	-238841	-10.05
Hohhot	82.18	2.51	610265	25.92	108191	17.29	78532	25.64	423542	29.77
Jinan	161.03	1.34	405565	20.44	388873	20.15	8516	30.20	8176	32.30
Lanzhou	57.73	1.15	589477	29.03	174466	29.18	49055	30.30	365956	28.79
Nanjing	191.62	1.16	-88684	-3.05	-73297	-2.91	-13790	-3.98	-1597	-3.37
Urumqi	60.98	1.05	608813	34.24	109925	38.05	74779	42.31	424109	32.32
Xining	31.03	1.39	424016	21.97	81103	22.39	52099	22.21	290814	21.80
Yinchuan	29.74	1.77	237618	24.85	107086	19.29	46222	38.42	84310	30.01

Table 4.4. Statistics of the integrated map of joint changes in NPP and GDP.

DN value	NPP	GDP	Percentages in whole territory of China	Percentages in established developed areas	Percentages in newly developed areas
1	Increase	No change	38.19%	0.77%	1.31%
2	Decrease	No change	18.75%	0.45%	1.00%
3	No change	Increase	1.12%	7.53%	1.33%
4	No change	Decrease	0.14%	0.42%	0.15%
5	Increase	Decrease	0.66%	4.48%	0.07%
6	Decrease	Increase	3.99%	19.10%	23.61%
7	Increase	Increase	12.89%	64.11%	70.21%
8	Decrease	Decrease	0.31%	1.86%	0.04%
9	No change	No change	23.96%	1.29%	2.28%

Land cover change

In images of the Land Cover Type 4, 1,152,003 km^2 of forest (32.24% of the total forested area in 2001) was converted to grass, but only 483,075 km^2 of grassland was converted to forestland (Table 3.1). Consequently the area of forest decreased 642,043 km^2 at a rate of 17.97%. Extensive areas of forest (1,152,003 km^2) and barren land (193,449 km^2) were changed to grass. These areas are much larger than those converting from grass to forest (483,075 km^2) and from grass to barren land (109,855 km^2) (Table 3.1). So the area of grass increased 753,959 km^2 at a rate of 23.14% and the area of vegetated land increased 111,916 km^2 at a rate of 1.64%. Barren land was converted to forest (80,945 km^2) and grass (193,449 km^2) while only 54,701 km^2 of forest and 109,855 km^2 of grass was converted to barren land. Two thousand one hundred and thirty seven (2, 137) km^2 of built-up land was converted to other types of land. Most of the built-up land was converted to forest (650 km^2) and grass (1,438 km^2). Yet, only 103 km^2 of built-up land in 2007 was converted from other types of lands (Table 3.1). Consequently the area of built-up land decreased notably.

In established developed areas, China's forestland decreased 33.88% in area, but a 49.59% increase in the area of grassland results in a 0.81% increase in vegetated land. Additionally, China experienced a 27.86% decrease in the area of barren land, and a 1.58% decrease in the area of built-up land from 2001 to 2007. In newly developed areas, similar land-cover changes occurred, i.e. a 37.24% increase in the area of grassland, a 26.69% decrease in the area of forestland, a 0.73% increase in the area of vegetated land, a 17.10% decrease in the area of barren land, and a 2.14% decrease in the area of built-up land.

In established or newly developed areas, most (28 out of 31) provinces experienced increases in the area of grass and decreases in the area of forest except Jilin, Gansu, and Xinjiang (Table 4.5). In developed areas of Jilin, the area of grass decreased while that of forest increased. In developed areas of Gansu, the area of grass and forest both increased. Xinjiang experienced simultaneous increase in the area of grass and forest in its established areas, but in its newly developed areas the area of grass decreased and that of forest increased (Table 4.5). Due to larger increased areas of grassland than decreased areas of forestland, most (28 out of 31) provinces experienced increases in vegetated land in their established or newly developed regions except Yunnan, Tianjin, and Shanxi with very small decreases of 6 km^2 (in established and newly developed areas overall), 2 km^2 (in newly developed areas), and 1 km^2 (in newly developed areas) respectively. Additionally, nearly all provinces experienced decreases in the area of barren land in their established or newly developed areas except Beijing with no change in the area of barren land (Table 4.5).

With tremendous economic growth, notable patterns of urban sprawl emerged in nearly all provinces and were reflected by large increases in lit area (Table 4.1). (Shanghai is the only exception to this pattern having experienced no change in lit area from 2001 to 2007. Shanghai is the most developed region in China and a relatively small municipality where, in 2001, all land suitable for human settlement and production was already developed.) The area of built-up land should have increased in accordance with the expansion of lit area, but the data show that 26 out of 31 provinces experienced decreases or no change in the area of built-up land. Even though the area of built-up land increased in a few provinces, the increase is small (Table 4.5). Only Hebei and Anhui experienced relatively large increases in the area of built-up land (49 km^2 and 17 km^2 respectively). Even in newly developed regions 19 provinces experienced decreases in the area of built-up land and 5 provinces did not experience any changes in the area of built-up land. Only 7 provinces experienced increases in the area of built-up land, and the increase in area is very small (Table 4.5). (The largest area of increase is only 6 km^2 in Yunnan). Detailed discussion of the contradictions between increases in lit area and decreases in built-up land is made in the next chapter.

At the city level changing patterns of land cover are almost the same with those at the national and the province levels. In either established or newly developed areas, most (8 out of 10) of the cities experienced decreases in the area of barren land and forest and increases in the area of grass (Table 4.6). In Hohhot's established and newly developed regions, the area of forest increased while the area of grass decreased. In Urumqi's established developed regions the area of grass and forest both increased while in newly developed regions the area of forest increased and the area of grass decreased. Most cities (7 out of 10) experienced increase in the area of vegetated land in their developed areas except Guangzhou (with an 11 km^2 decrease), Jinan (with a 7 km^2 decrease), and Xining (with a 7 km^2 decrease). In established developed areas, half of the cities (i.e. Guangzhou, Hangzhou, Hohhot, Lanzhou, and Nanjing) experienced decreases in the area of built-up land and the other half of the cities (i.e. Fuzhou, Jinan, Urumqi, Xining, and Yinchuan) experienced increases in the area of built-up land. Moreover, the increases in the area of built-up land are relatively small. The largest increase in area is only 8 km^2 in Urumqi. In newly developed areas, the cities experienced no change or very small changes in the area of built-up land. Thus, from 2001 to 2007 land-cover-change patterns in established and newly developed areas include decreases in the area of barren land and built-up land, while the area of vegetated lands increased. Moreover, the changing patterns of land cover are mostly consistent across different geographic scales (national, province, and city scales).

Table 4.5. Land cover changes in developed areas for 31 provinces.

Province	In established developed areas (km^2)					In newly developed areas (km^2)				
	Forest	Grass	Barren land	Built-up	Vegetated land	Forest	Grass	Barren land	Built-up	Vegetated land
Anhui	-11899	11989	-129	18	90	-9240	9322	-79	-1	82
Beijing	-2735	2760	0	-24	25	-41	41	0	1	0
Chongqing	-2870	3121	-163	-89	250	-2591	2768	-166	-7	176
Fujiang	-2042	2392	-305	-23	350	-526	581	-45	-5	55
Gansu	649	128	-774	-5	777	165	305	-478	2	470
Guangdong	-5161	6261	-882	-163	1100	-2214	2313	-98	2	99
Guangxi	-6066	6195	-83	-30	129	-2855	2911	-49	-3	57
Guizhou	-2203	2244	-2	-24	41	-1553	1563	-2	-5	9
Hainan	-726	780	-40	-3	53	-206	224	-15	-2	18
Heibei	-22210	22256	-96	46	46	-1530	1540	-3	3	9
Heilongjiang	-160	282	-116	-3	123	-142	227	-72	-8	85
Henan	-27548	27628	-80	-46	80	-4882	4896	-22	-4	14
Hubei	-4115	4440	-135	-196	324	-1702	1798	-65	-35	96
Hunan	-10897	11085	-43	-149	188	-8159	8226	-27	-44	67
Inner Mongolia	-219	1413	-1211	-6	1194	-840	1664	-832	5	825
Jiangsu	-21480	21980	-362	-119	500	-4076	4122	-34	0	46
Jiangxi	-2817	2875	-32	-26	58	-2061	2113	-55	-1	53
Jilin	1125	-1056	-59	-2	69	232	-181	-44	-2	51
Liaoning	-13181	13671	-464	0	489	-4068	4132	-65	-2	65
Ningxia	-1273	1535	-268	2	262	-1022	1102	-83	-2	80
Qinghai	-331	444	-119	2	113	-280	446	-167	-2	166
Shaanxi	-282	370	-78	-22	88	-2510	2601	-88	-4	91
Shandong	-48251	48646	-356	-3	395	-2914	2923	-7	-3	9
Shanghai	-82	155	-25	-30	72	0	0	0	0	0

Table 4.5 Continued. Land cover changes in developed areas for 31 provinces.

Province	In established developed areas (km^2)					In newly developed areas (km^2)				
	Forest	Grass	Barren land	Built-up	Vegetated land	Forest	Grass	Barren land	Built-up	Vegetated land
Shanxi	-6406	6486	-42	-29	81	-1984	1983	-2	-1	-1
Sichuan	-12992	13293	-87	-212	301	-9906	10028	-84	-35	122
Tianjin	-2105	2125	-20	6	20	-10	9	0	0	-2
Tibet	-55	62	-7	0	7	-111	116	-6	0	5
Xinjiang	848	415	-1268	6	1263	973	-375	-597	2	598
Yunnan	-6593	6591	-3	0	-2	-5311	5307	-6	6	-4
Zhejiang	-5210	5636	-140	-279	426	-920	932	-7	0	12
Sum	-217288	226202	-7389	-1403	8914	-70285	73637	-3198	-144	3352

Table 4.6. Land cover changes in developed areas for the 10 selected cities.

City	In old developed areas (km^2)					In new developed areas (km^2)				
	Forest	Grass	Barren land	Built-up	Vegetated land	Forest	Grass	Barren land	Built-up	Vegetated land
Fuzhou	-256	363	-100	1	107	-25	41	-12	-1	16
Guangzhou	-233	369	-98	-17	136	-21	10	0	0	-11
Hangzhou	-721	830	-11	-114	109	-84	86	0	0	2
Hohhot	268	-138	-116	-1	130	93	-66	-25	1	27
Jinan	-3451	3444	-4	3	-7	-51	53	0	0	2
Lanzhou	-204	263	-27	-3	59	-3	19	-22	0	16
Nanjing	-168	217	-41	-22	49	-70	86	-1	0	16
Urumqi	83	29	-124	8	112	148	-140	-9	-1	8
Xining	-159	152	0	2	-7	-90	93	-1	-2	3
Yinchuan	-485	545	-57	5	60	-368	385	-21	-3	17

V. DISCUSSION

Contradictions between increase in lit area and decrease in built-up land

With rapid development of its economy, China experienced remarkable urbanization after the economic reform in 1978 (Chen, 2007; Liu, 2006). A large number of rural people migrated to cities to seek high-payment jobs (Liang, 2001). From 2001 to 2007, China's urban population increased from 480.64 million to 606.33 million (National Bureau of Statistics of China, 2002; 2008). It seems reasonable to assume that the increase in urban population and the rise in individual income would lead to an increase in demand for housing which would lead to an increase in built-up land. However, remotely sensed data indicate that China's lit area increased by 449,675 km^2 while built-up land decreased 3,508 km^2 and 674 km^2 in established and newly developed areas, respectively. The increased lit area and decreased built-up land seem contradictory.

A possible explanation of this apparent contradiction is the expected outcome of Chinese co-development policies. Since 1987, the Chinese government began to liberalize its economy and to develop commercial residential communities (Hu and Kaplan, 2001). With rapid increases in income, the Chinese people had greater expectations for the quality of their living environment. Previous studies (Hu and Kaplan, 2001; Jim and Chen, 2006a; Jim and Chen, 2006b) found that large areas of suburban lands were used to establish new commercial residential communities and many old residential communities were reconstructed as new commercial residential communities. Additionally, Kong and Nakagoshi (2006) and Li et al. (2005) pointed out that in the process of urban development local governments have paid much attention to establishing green spaces, included vegetated boulevards along road networks. Whereas old residential communities were mainly composed of housing and paved roads, new commercial residential communities contain large green spaces (Figure 5.1).

In the MODIS land cover products built-up lands are mainly composed of buildings and impervious surfaces (Belward et al., 1999; Scepan, 1999; Friedl et al., 2002; Friedl et al., 2010). New commercial residential communities are likely defined as green-space pixels because in such communities built-up land makes up an increasingly smaller proportion of the overall land cover. This situation would lead to pixels being reclassified from built-up land to grass or forest. The construction of green-spaces likely led to decreases in the area of identified built-up land. Therefore, the increase in lit area reflects China's economic and urban development while the decrease in built-up land suggests the development of urban ecological amenities. Explained in this way, the apparent contradiction between increased lit area and decreased built-up land partly reflects the achievement of co-development of economy and environment in China.

An additional factor that may partially explain the apparent contradiction of increases in lit area and decreases in built-up land is the accuracy of the land cover product. Despite continual improvements in the classification methodology, errors still arise is classification products. Improvements in the MODIS 5 classification methodology include an enhanced training site database, the incorporation of surface temperature, and the incorporation of additional ancillary data (Friedl et al., 2010). Moreover, the classification algorithm has been improved to reduce year-to-year variation in land-cover labels. But despite the improvements the overall product accuracy is approximately 75% and there are large class-specific variations (Friedl et al., 2010). Thus, it is certainly in the realm of possibility that a portion of the decrease in built-up land is due to systematic error in the land cover product itself. I contend, however, that the clear decrease in the built-up land cover class across much of China is attributable to actual changes on the ground that are attributable to enhanced urban green spaces.

Figure 5.1. A green garden community in China.

Impacts of anthropogenic factors on ecosystem production

Although anthropogenic activities are dominant factors affecting ecosystem production in developed areas, there is a possibility that natural factors (e.g., climate warming and increased precipitation) led to increases in NPP that outpaced decreases in NPP driven by economic growth from 2001 to 2007. To examine the suitability of the

IPAT theory and to explore actual outcomes of Chinese co-development policy, the actual drivers of changes in NPP need to be fully discussed.

Natural forces (e.g. temperature and precipitation) often produce uneven ecosystem production across large geographic extents. Yet, in a relatively small area (e.g. a city) natural factors should equally affect NPP changes in developed and undeveloped areas. In China, similar annual variations in NPP in established developed, newly developed, and undeveloped areas proximate to developed areas are evidence that natural factors equally affect NPP in small areas. Previous studies have demonstrated that luminosity of nighttime lights is a good proxy for economy and population (Bharti et al., 2011; Chen and Nordhaus, 2011; Henderson et al., 2011). Since developed and undeveloped areas in this study were delimited based on the existence of stable nighttime lights, the population and stable socioeconomic activities in the developed areas should be greater than those in undeveloped areas. The IPAT theory maintains that the larger a population and the greater the number of socioeconomic activities present in an area, the greater the negative environmental impacts (Chertow, 2000). Thus, if natural factors equally affect changes of NPP in developed and neighboring undeveloped areas then ecosystem production should be greater in undeveloped areas than in developed areas. However, actual ecosystem production at the city scale is often opposite to what the IPAT theory suggests, as outlined in the paragraphs below.

Four cities (Fuzhou, Lanzhou, Urumqi, and Xining) had larger percentage increases of NPP in developed areas than in undeveloped areas (Table 4.3). Hangzhou had a smaller percentage decrease of NPP in established and newly developed areas (-2.03% and -6.89% respectively) than that in undeveloped areas (-10.05%). Guangzhou experienced a decrease in NPP (-5.70%) in its undeveloped areas, yet in established developed areas NPP increased. Although NPP decreased in newly developed areas of Guangzhou, the percentage decrease (-1.48%) is smaller than that in undeveloped areas. Since most stable socioeconomic activities occur in the developed areas rather than in the undeveloped areas, it appears that the stable socioeconomic activities coincide with greater ecosystem production in the above six cities (i.e. Fuzhou, Lanzhou, Urumqi, Xining, Hangzhou, and Guangzhou). The trends in each of these cities contradicts the IPAT expectation by indicating an increase in NPP where human activity is greatest. These trends suggest the achievement of the outcomes expected by co-development policies.

Hohhot, Jinan, and Yinchuan experienced increases in NPP in their undeveloped, established developed, and newly developed areas. The percentage increases of NPP in undeveloped areas are larger than those in established and newly developed areas (Table 4.3). Consequently, human activities in these three cities coincide with a reduction in ecosystem production and suggest the outcomes expected by the IPAT equation rather than those of co-development policies.

The situation is mixed in Nanjing and neither the IPAT expectations nor the Chinese co-development policy expectations are evident. Nanjing experienced decreases in NPP in its undeveloped, established developed, and newly developed areas. The percentage decrease of NPP in undeveloped areas (-3.37%) is larger than that in established developed areas (-2.91%) but smaller than in newly developed areas (-3.98%). Thus, it cannot be confirmed whether human activities in Nanjing promoted or reduced ecosystem production.

The emergent pattern in the six cities is that of greater ecosystem production in developed areas than in undeveloped areas, which supports the ideas that stable socioeconomic activities and consequent economic growth promote increased ecosystem production. In contrast, three cities experienced changes in NPP consistent with the assertion of the IPAT theory that stable socioeconomic activities and associated economic growth produce adverse impacts on ecosystem production.

Moreover, figure 3.4 shows that Beijing, Guangdong, and Jiangxi experienced large decreases in NPP (covering most of each province), which implies that natural factors negatively impacted ecosystem production across the extent of each province. Consequently, without human impacts NPP in undeveloped and developed areas should both decrease in the three provinces. However, the actual situation is that NPP in undeveloped areas of these three provinces decreased, but it increased in established and/or newly developed areas that are surrounded by the undeveloped areas (Table 4.2). The changing patterns of NPP in these three provinces support the ideas that stable socioeconomic activities and associated economic growth promote but not reduce ecosystem production. These cases, therefore, appear to provide some support at the province level for the hypothesis that economic growth may produce positive rather than negative impacts on ecosystem production.

A potential alternative explanation for larger decreases of NPP in undeveloped areas than developed areas is that increased GDP, and greater demand for goods in developed areas, drives resource extraction in neighboring undeveloped areas. Distant outcomes of human activity have been well documented in other regions (Liu et al., 2013; Liu and Yang, 2013; Eakin et al., 2014), but are not explicitly considered here. Most raw resources from undeveloped areas certainly account for a majority of the resources used in developed areas (e.g., timber, minerals, crops), and greater demand in urban areas would increase pressure on ecosystem production in undeveloped areas, so this could be an important consideration for future analysis.

Dynamics of the coupled increases in GDP and NPP

Based on the IPAT theory, China's rapid economic growth should lead to reduced ecosystem production because population and income growth inevitably increase the consumption of material products (Imhoff et al., 2004). Consequently, consuming more material products should mean larger amounts of NPP appropriated for human use (Imhoff et al., 2004). Additionally, population and income growth lead to increases in the demand for living space, and consequently large areas of green spaces are converted to built-up land. The disappearance of green spaces results in a decrease in NPP, even though global climate warming may promote ecosystem production (Zhao and Running, 2010). Hence, an irreconcilable contradiction seems to exist between simultaneous increases in GDP and NPP.

The actual situation, however, demonstrates that developed areas experiencing coupled increases in GDP and NPP are more numerous than those experiencing increases in GDP and decreases in NPP during the period 2001 to 2007, even when accounting for background variations in NPP (i.e., changes in NPP in undeveloped areas surrounding developed areas). Economic growth did not lead to an extensive disappearance of vegetated lands in developed areas. In fact, in most cities ecosystem production is greater in developed areas where a large number of stable economic activities exist than in undeveloped areas that lack stable economic activities.

In the 2000s, with increasingly high incomes, ordinary Chinese citizens had higher expectations for the quality of their living environment (Hu and Kaplan, 2001; Jim and Chen, 2006a; Jim and Chen, 2006b; Qin et al, 2004) and large areas of urban green spaces were created for leisure and entertainment (Jim and Chen, 2006a; Kong and Nakagoshi, 2006). More importantly, the Chinese government implemented sustainable co-development policy to replace previous policies of "economic development first, environmental restoration later" (Liu, 2010). The Chinese government had accumulated wealth from the more than twenty-year period of economic growth (from the 1978 economic reform to 2000), so into the 2000s the government had sufficient funding to maintain and restore ecosystems (Liu et al., 2008). Additionally, with implementation of the co-development policy, environmental protection and economic growth both became principal criteria to evaluate local government officials' performance and promotion (Zhou, 2002). To obtain promotion, the local government officials had to increase funding for protection and maintenance of ecosystems (Geng, 2011). Many grasslands and forestlands have been planted which increased NPP in the local ecosystems (Xu, 2011).

All of these changes in GDP, NPP, and land cover suggest that economic growth only rarely accompanied negative impacts on ecosystem production. In fact, economic growth was more likely to accompany positive impacts on ecosystem production in developed areas. It is not yet clear if the lower NPP in undeveloped areas immediately adjacent to developed areas is attributable to increasing GDP in developed areas. It is, however, plausible that co-development policy leads to increased green-space in developed areas (as desired by policy-makers) while simultaneously decreasing ecosystem production in neighboring undeveloped areas.

Reconsidering IPAT and revising the EKC

This study shows that, in most Chinese provinces and the selected cities, the number of developed areas experiencing coupled increases in GDP and NPP was greater than those experiencing increases in GDP and decreases in NPP from 2001 to 2007. Moreover, in most selected cities stable socioeconomic activities did not reduce ecosystem production. These results contradict traditional IPAT theory and necessitate a reconsideration of it.

The IPAT theory was proposed in the 1970s, a period with rapid population growth, economic growth and technology development, and when many case studies were presented in support of the IPAT theory. A few studies, however, showed that after a region's economy reached a certain high level, economic growth produced increasingly smaller adverse impacts on the environment (Dietz and Roas, 1997; Grossman and Krueger, 1995; Kuznets, 1995; Martinez-Zarzoso et al., 2007; Stern, 2004). The findings in the present research suggest that not only might some of the adverse impacts diminish, but that even some positive environmental impacts may appear.

With continued economic growth across the globe expected in future and the findings about human-environment relationships in China presented herein, the basic tenets of the IPAT theory need to be reconsidered. The claim of the IPAT theory that economic growth always produces negative impacts on environmental quality is called into question. Economic growth can produce negative or positive impacts at different levels of affluence. The IPAT equation does not fully describe the relationship between environment quality and economic development and a revised EKC may more fully capture the dynamics of the relationship between IPAT variables (Figure 5.2). The present EKC illustrates that various negative environmental impacts tend to increase with economic growth until average income reaches a threshold value, after which negative environmental impacts begin to decline. I suggest an extension to the EKC where not only do negative impacts decrease at greater average incomes, but where some negative impacts are replaced by positive impacts. High average incomes have been shown to correlate to pollution reduction, but not to eliminate it entirely (Keene and Deller, 2013). My addition to the EKC concept is that with increasingly high incomes there is greater demand for improved environmental quality such that some negative environmental impacts are replaced by positive environmental impacts. This modification to the EKC concept is supported by the case of Chinese co-development as presented in this dissertation.

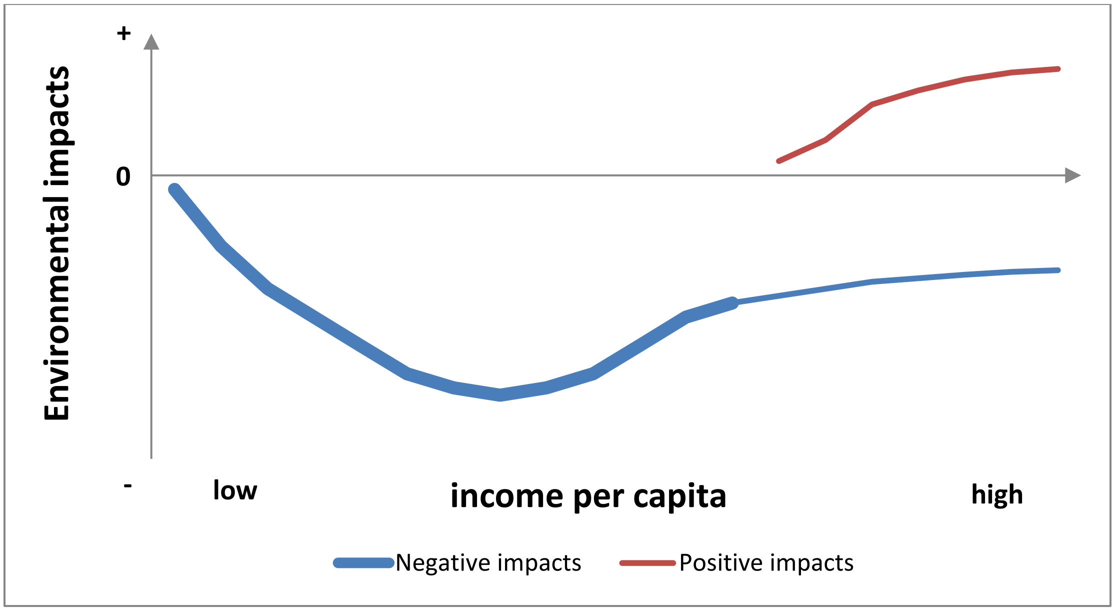

Figure 5.2. Schematic of modified Environmental Kuznet's Curve.

VI. CONCLUSIONS

Sustainable co-development of economy and environment has been established as a national policy of the present Chinese government. The goal of this dissertation has been to study the actual outcomes of co-development policy using GDP as an indicator of economic development and NPP as an indicator of environmental productivity. Uncovering the relationship between China's economic growth and changes its environmental productivity not only contributes to an evaluation of the outcomes of co-development policies but permits a critical reexamination of the IPAT and Environmental Kuznet's Curve models of human-environment interactions. An essential tenet of the IPAT theory is that economic growth will inevitably produce negative impacts on the environment. The EKC suggests that at high levels of economic growth negative environmental impacts will decrease. This research examines the particular case of China's changes in GDP and NPP before and after implementation of its co-development policies.

Remotely sensed data and demographic data were used to analyze spatio-temporal change in coupled NPP-GDP patterns in China. Census-based GDP data reported at the province level were spatially disaggregated to 1 km × 1 km pixels using DMSP-OLS nighttime lights imagery and the LandScan population dataset, creating a GDP dataset with a spatial resolution matching the MODIS NPP dataset. Pixel-level GDP and NPP data were then aggregated to the city level which enabled multi-scale analyses of GDP and NPP.

The multi-level GDP and NPP datasets were used to assess the actual outcomes of Chinese co-development policies and to test the assumptions of the IPAT theory for the case of China. According to IPAT theory economic growth inevitably generates negative impacts on a local environment and economic growth should quantitatively correlate to the magnitude of negative environmental impacts (Alcott, 2010). Consequently, increases in GDP should lead to proportional decreases in NPP, especially in developed areas where human's activities (rather than natural factors) are the dominant influences on ecosystem production. However, from these analyses of integrated GDP-NPP change, I found that from 2001 to 2007 most Chinese developed areas experienced coupled increases in GDP and NPP across different geographic scales but the total changes (or percentage changes) of GDP did not significantly correlate with the total changes (or percentage changes) of NPP. The lack of significant correlations was attributable to large variations in the magnitude of GDP changes in different regions of China. For most of the selected cities ecosystem productivity was greater in developed areas where a large number of stable socioeconomic activities exist than in undeveloped areas where stable socioeconomic activities rarely exist. Vegetated land tended to increase in developed areas. These joint GDP-NPP and land-cover changes reflect that in many areas of China economic growth from 2001 to 2007 is accompanied by positive impacts on ecosystems production instead of negative impacts.

The findings of this research suggest that some of the outcomes expected from the implementation of China's co-development policies are apparent. With increases in average income, Chinese citizens had higher expectations for their quality of life and their environment. In such a socioeconomic context, the Chinese government promulgated and implemented their co-development policies. According to IPAT an increase in affluence leads to greater negative environmental impacts. However, this study finds that few provinces and cities experienced economic growth coupled with reduced NPP. On the contrary, most provinces and cities experienced increased NPP that exceeds the amount of NPP in neighboring undeveloped regions. Since the IPAT theory cannot explain the effects of economic growth on ecosystem production in these areas, it must be modified. I propose a revised EKC to show the relationship between economic development and environmental productivity based on the findings for China. At relatively low affluence levels, economic growth produces negative impacts on environmental quality. The negative impacts of economic growth on environmental quality appear to reach maximums at high levels of affluence and decline at even higher levels of affluence. With further increase in affluence, some negative impacts may disappear while some positive impacts emerge.

REFERENCES

Alberti, M. 2008. Advances in Urban Ecology: Integrating humans and ecological processes into urban ecosystems. Springer Science, New York, NY, USA.

Anderson, D.R. 2008. Model based inference in the life sciences: A primer on evidence. Springer-Verlag, New York, NY, pp.997-1010.

Amaral, S., G. Camara, A.M.V. Monteiro, J.A. Quintanilha, C.D. Elvidge. 2005. Estimating population and energy consumption in Brazilian Amazonia using DMSP night-time satellite data. *Computer, Environment and Urban Systems*, 29:179-195.

Baugh, K., C. Elvidge, T. Ghosh, D. Ziskin. 2010. Development of a 2009 Stable Lights Product using DMSP-OLS data. *Proceedings of the 30th Asia-Pacific Advanced Network Meeting*, pp. 114-130.

Belward, A.S., J.E. Estes, K.D. Kline. 1999. The IGBP-DIS global 1-km land-cover data set DIScover: a project overview. *Photogrammetric Engineering and Remote Sensing*, 65:1013-1020.

Bhaduri, B.L., E.A. Bright, P.R. Coleman, J.E. Dobson. 2002. LandScan: locating people is what matters. *Geoinformatics*, 5:34-37.

Bharti, N., A.J. Tatem, M.J. Ferrari, R.F. Grais, A. Djibo, B.T. Grenfell. 2011. Explaining seasonal fluctuations of measles in Niger using nighttime lights imagery. Science, 334:1424-1427.

Cao, X., J. Chen, H. Imura, O. Higashi. 2009. A SVM-based method to extract urban areas from DMSP-OLS and SPOT VGT data. *Remote Sensing of Environment*, 113:2205-2209.

Chand, T.R.K., K.V.S. Badarinarh, C.D. Elvidge, B.T. Tuttle. 2009. Spatial characterization of electrical power consumption patterns over India using temporal DMSP-OLS night-time satellite data. *International Journal of Remote Sensing*, 30:647-661.

Chase, T.N., R.A. Pielke, T.G.F. Kittel, R.R. Nemani, S.W. Running. 1999. Simulated impacts of historical land cover changes on global climate in northern winter. *Climate Dynamics*, 16:93-105.

Chen, J. 2007. Rapid urbanization in China: a real challenge to soil protection and food security. *Catena*, 69:1-15.

Chen, J.M., B. Chen, K. Higuchi, J. Liu, D. Chan, D. Worthy, P. Tans, A. Black. 2006. Boreal ecosystems sequestered more carbon in warmer years. *Geophysical Research Letters*, 33: L10803.

Chen, X., W. D. Nordhaus. 2011. Using luminosity data as a proxy for economic statistics. *PNAS*, 108(21):8589-8594.

Chertow, M.R. 2000. The IPAT equation and its variants. *Journal of Industrial Ecology*, 4:13-29.

Cheriyadat, A., E.A. Bright, B. Bhaduri, D. Potere. 2007. Mapping of settlements in high resolution satellite imagery using high performance computing. *Geojournal*, 69:119-129.

Commoner, B., M. Corr, P.J. Stamler. 1971. The closing circle: nature, man and technology. New York: Knopf.

Commoner, B. 1972. The environmental cost of economic growth. In population, resources and the Environment, edited by R.G. Ridker. Washington DC: U.S. Government Printing Office, pp.339-363.

Croft, T. A. 1973. Burning Waste Gas in Oil Fields. *Nature*, 245:375-376.

Darwin, C. 1859. The origin of species by means of natural selection. Penguin Classics, London.

Denko, D.M. 1992. The digital chart of the world project. Photogrammetric Engineering & Remote Sensing, 58:1125-1128.

Dietz, T., E.A. Rosa. 1997. Effects of population and affluence on CO_2 emissions. *PNAS*, 94:175-179.

Dobson, J.E., E.A. Bright, P.R. Coleman, R.C. Durfee, B.A. Worley. 2000. A global population database for estimating populations at risk. *Photogrammetric Engineering & Remote Sensing*, 66:849-857.

Doll, C.N.H., J.P. Muller, C.D. Elvidge. 2000. Night-time imagery as a tool for global mapping of socio-economic parameters and greenhouse gas emissions. *Ambio*, 29:157-162.

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

Doll, C.N.H. 2008. CIESIN Thematic guide to night-time light remote sensing and its applications. Available from: http://sedac.ciesin.columbia.edu/tg/. (last accessed 14 January 2014).

Eakin, H.C., M.C. Lemos, D.R. Nelson. 2014. Differentiating capacities as a means to sustainable climate change adaptation. *Global Environmental Change*, 27:1-8.

Earth Observation Group. 2010. Global DMSP-OLS nighttime lights time series 1992-2008 (Version 4). Available from: http://www.ngdc.noaa.gov/dmsp/download.html. (last accessed 14 January 2014).

Ehrlich, P.R., J.P. Holdren. 1971. Impact of population growth. *Science*, 171:1212-1217.

Ehrlich, P.R., J.P. Holdren. 1972. Impact of population growth. In population, resources, and the environment, edited by R.G. Riker. Washington DC: U.S. Government Printing Office. Pp. 365-377.

Elvidge, C.D., K.E. Baugh, E.A. Kihn, H.W. Kroehl, E.R. Davis, C. Davis. 1997a. Relation between satellite observed visible - near infrared emissions, population, and energy consumption. *International Journal of Remote Sensing*, 18:1373-1379.

Elvidge, C.D., K.E. Baugh, E.A. Kihn, H.W. Kroehl, E.R. Davis. 1997b. Mapping of City Lights Using DMSP Operational Linescan System data. *Photogrammetric Engineering and Remote Sensing*, 63:727-734.

Elvidge,C.D., K.E. Baugh, J.B. Dietz, T. Bland, P.C. Sutton, H.W. Kroehl. 1999. Radiance Calibration of DMSP-OLS Low-light Imaging Data of Human Settlements. *Remote Sensing of Environment*, 68:77-88.

Elvidge C.D., P.C. Sutton, T. Ghosh, B.T. Tuttle, K.E. Baugh, B. Bhaduri, E. Bright. 2009a. A global poverty map derived from satellite data. *Computer & Geosciences*, 35:1652-1660.

Elvidge, C.D., D. Ziskin, K.E. Bough, B.T. Tuttle, T. Ghosh, D.W. Pack, E.H. Erwin, M. Zhizhin. 2009b. A fifteen year record of global natural gas flaring derived from satellite data. *Energies*, 2:595-622.

Friedl, M.A., D.K. Mclver, J.C.F. Hodges, X.Y. Zhang, D. Muchoney, A.H. Strahler, C.E. Woodcock, S. Gopal, A. Schneider, A. Cooper, A. Baccini, F. Gao, C. Schaaf. 2002. Global land cover mapping from MODIS: algorithms and early results. *Remote Sensing of Environment*, 83:287-302.

Friedl, M.A., D. Sulla-Mensshe, B. Tan, A. Schneider, N. Ramankutty, A. Sibley, X. Huang. 2010. MODIS collection 5 global land cover: algorithm refinements and characterization of new datasets. *Remote Sensing of Environment*, 114:168-182.

Friedl, M.A., D. Sulla-Mensshe. 2011. Note to users of MODIS Land Cover (MCD12Q1) Products. Available from: http://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD12 (last accessed 9 May 2014).

Fujita, M., D. Hu. 2001. Regional disparity in China 1985-1994: the effects of globalization and economic liberalization. *The Annals of Regional science*, 35:3-37.

Gallo, K.P., C.D. Elvidge, L. Yang, B.C. Reed. 2004. Trends in night-time city lights and vegetation indices associated with urbanization within the conterminous USA. *International Journal of Remote Sensing*, 20:2003-2007.

Geng, Y. 2011. Improve China's sustainability targets. *Nature*, 477:162.

Ghosh, T., S. Anderson, R.L. Powell, P.C. Sutton, C.D. Elvidge. 2009a. Estimation of Mexico's informal economy and remittances using nighttime imagery. *Remote Sensing*, 1:418-444.

Ghosh, T., C.D. Elvidge, P.C. Sutton, K.E. Baugh, D. Ziskin, B.T. Tuttle. 2010a. Creating a global grid of distributed fossil fuel CO_2 emissions from nighttime satellite imagery. *Energies*, 3:1895-1913.

Ghosh, T., R.L. Powell, C.D. Elvidge, K.E. Baugh, P.C. Sutton, S. Anderson. 2010b. Shedding light on the global distribution of economic activity. *The Open Geography Journal*, 3:147-160.

Ghosh, T., P. Sutton, R. Powell, S. Anderson, C.D. Elvidge. 2009b. Estimation of Mexico's informal economy using DMSP nighttime lights data. *IEEE Proceedings of the 7th International Urban Remote Sensing Conference*. Available from: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5137751 (last accessed 14 January 2014).

Global Land Cover Facility. 2011. AVHRR, Global Production Efficiency Model: Summed Annual Global NPP. Available from: http://glcfapp.glcf.umd.edu:8080/esdi/index.jsp?productID=6 (last accessed 14 January 2014).

Grossman, G.M., A.B. Krueger. 1995. Economic growth and the environment. *The Quarterly Journal of Economics*, 110:353-377.

Gurney, K.R., D.L. Mendoza, Y. Zhou, M.L. Fischer, C.C. Miller, S. Geethakumar, S.D.L.R.D. Can. 2009. High resolution fossil fuel combustion CO_2 emission fluxes for the United States. *Environmental Science & Technology*, 43:5535-5541.

GLP. 2005. Science Plan and Implementation Strategy. IGBP Report No. 53/IHDP Report No. 19. IGBP Secretariat, Stockholm, 64pp.

Haberl. H. 1997. Human appropriation of net primary production as an environmental indicator: implications for sustainable development. *Ambio*, 26:143-146.

Haberl, H., N.B. Schulz, C. Plutzar, K.H. Erb, F. Krausmann, W. Loibl, D. Moser, N. Sauberer, H. Weisz, H.G. Zechmeister, P. Zulka. 2004. Human appropriation of net primary production and species diversity in agricultural landscapes. *Agriculture, Ecosystems & Environment*, 102:213-218.

Harbaugh, W.T., A. Levinson, D.M. Wilson. 2002. Reexamining the empirical evidence for an environmental Kuznets curve. *The Review of Economics and Statistics*, 84:541-551.

Harrison, P. 1993. The third revolution: population, environment and a sustainable world. Penguin Books Ltd., London.

Henderson, V., A. Storeygard, D.N. Weil. 2011. A bright idea for measuring economic growth. *American Economic Review*, 101(3):194-199.

Holling, C.S., 1973. Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, 4:1-23.

Houghton, R.A., J.L. Hackler, K.T. Lawrence. 1999. The U.S. carbon budget: contribution from land-use change. Science, 285:574-578.

Hu, X, D.H. Kaplan. 2001. The emergence of affluence in Beijing: residential social stratification in China's capital city. *Urban Geography*, 22:54-77.

Hubacek, K., D. Guan, A. Barua. 2007. Chaning lifestyles and consumption patterns in developing countries: a scenario analysis for China and India. *Futures*, 39:1094-1096.

Hulme, M. E.M. Barrow, N.W. Arnell, P.A. Harrison, T.C. Johns, T.E. Downing. 1999. Relative impacts of human-induced climate change and natural climate variability. *Nature*, 397:688-691.

Hubacek, K., L. Sun. 2001. A scenario analysis of China's land use and land cover change: incorporating biophysical information into input-output modeling. *Structural Change and Economic Dynamics*, 12:367-397.

Imhoof, M. L., L. Bounoua, T. Ricketts, C. Loucks, R. Harriss, W.T. Lawrence. 2004. Global patterns in human consumption of net primary production. *Nature*, 429:870-873.

Imhoff, M.L., W.T. Lawrence, C. Elvidge, T. Paul, E. Levine, M. Prevalsky, V. Brown. 1997a. Using nighttime DMSP-OLS images of city lights to estimate the impact of urban land use on soil resources in the U.S. *Remote Sensing of Environment* , 59:105-117.

Imhoff, M.L., W.T. Lawrence, D.C. Stutzer, C.D. Elvidge. 1997b. A Technique for Using Composite DMSP/OLS 'City Lights' Satellite Data to Accurately Map Urban Areas, *Remote Sensing of Environment*, 61:361-370.

Jensen, J., A. Saalfeld, F. Broome, D. Cowen, K. Price, D. Ramsey, L. Lapine. 2002. Spatial data acquisition and integration, UCGIS, 2002 research agenda, Long-term research challenges. Available from: http://www.ucgis.org/priorities/research/2002researchagenda.htm#longterm (last accessed 14 January 2014).

Jim, C.Y., W. Y. Chen. 2006a. Recreation-amenity use and contingent valuation of urban greenspaces in Guangzhou, China. *Landscape and Urban Planning*, 75:81-96.

Jim, C.Y., W. Y. Chen. 2006b. Perception and attitude of residents toward urban green spaces in Guangzhou (China). *Environmental Management*, 38:338-349.

Justice, C.O., J.R.G. Townshend, E.F. Vermote, E. Masuoka, R.E. Wolfe, N. Saleous, D.P. Roy, J.T. Morisette. 2002. An overview of MODIS land data processing and product status. *Remote Sensing of Environment*, 83:3-15.

Kauppi, P.E. J.H. Ausubel, J. Fang, A.S. Mather, R.A. Sedjo, P.E. Waggoner. 2006. Returning forests analyzed with the forest identity. *PNAS*, 103:17574-17579.

Keene, A. S.C. Deller. 2013. Evidence of the Environmental Kuznets' Curve among US counties and the impact of social capital. *International Regional Science Review*, published online before print, available from: http://irx.sagepub.com/content/early/2013/09/05/0160017613496633.abstract (last accessed 14 Jaunary 2014).

Keng, C.W.K. 2006. China's unbalanced economic growth. Journal of Contemporary China, 15:183-214.

Kong, F., N. Nakagoshi. 2006. Spatial-temporal gradient analysis of urban green spaces in Jinan, China. Landscape and Urban Planning, 78:147-164.

Kuznets, S. 1995. Economic growth and income inequality. *American Economic Review*, 49:1-28.

Lai, H.H. 2002. China's Western Development Program: Its rationale, implementation, and prospects. *Modern China*, 28: 432-466.

Lambin, E.F., B.L. Turner, J.G. Helmut, S.B. Agbola, A. Angelsen, J.W. Bruce, O.T. Coomes, R. Dirzo, G. Fischer, C. Folke, P.S. George, K. Homewood, J. Imbernon, R. Keeemans, X. Li, E.F. Moran, M. Mortimore, P.S. Ramakrishnan, J.F. Richards, H. Skanes, W. Steeffen, G.D. Stone, U. Svedin, T.A. Veldkamp, C. Vogel, J. Xu. 2001. The causes of land-use and land-cover change: moving beyond the myths. *Global Environmental Change*, 11:261-269.

Levin, S.A. 1998. Ecosystems and the biosphere as complex adaptive systems. *Ecosystems*, 1:431-436.

Leichenko, R.M., K.L. O'Brien. 2008. Environmental change and globalization—Double exposures. Oxford University Press, New York.

Li, F., R. Wang, J. Paulussen, X. Liu. 2005. Comprehensive concept planning of urban greening based on ecological principles: a case study in Beijing, China. *Landscape and Urban Planning*, 72:325-336.

Liang, Z. 2001. The age of migration in China. *Population and Development Review*, 27:499-524.

Liu, J. 2010. China's road to sustainability. *Science*, 328:50.

Liu, L. 2006. Urbanization in China: Erlitou and its hinterland. G. Storey (Ed.), Urbanism in the Preindustrial World, The University of Alabama Press, Tuscaloosa, pp.161-189.

Liu, J., J. Diamond. 2005. China's environment in a globalizing world. *Nature*, 435:1179-1186.

Liu, J., J. Diamond. 2008. Revolutionizing China's environmental protection. *Science*, 319:37-38.

Liu Z., C. He, Q. Zhang, Q. Huang, Y. Yang. 2012. Extracting the dynamics of urban expansion in China using DMSP-OLS nighttime light data from 1992 to 2008. *Landscape and Urban Planning*, 106:62-72.

Liu, J. V. Hull, M. Batistella, R. DeFries, T. Dietz, F. Fu, T.W. Hertel, R.C. Izaurralde, E. F. Lambin, S. Li, L.A. Martinelli, W. J. McConnell, E.F. Moran, R. Naylor, Z. Ouyang, K.R. Polenske, A. Reenberg, G.M. Rocha, C.S. Simmons, P.H. Verburg, P.M. Vitousek, F. Zhang, C. Zhu. 2013. Framing sustainability in a telecoupled world. *Ecology and Society*, 18(2): 26. http://dx.doi.org/10.5751/ES-05873-180226.

Liu, J., S. Li, Z. Ouyang, C. Tam, X. Chen. 2008. Ecological and socioeconomic effects of China's policies for ecosystem services. *PNAS*, 105:9477-9482.

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

Liu, M., H. Tian. 2010. China's land cover and land use change from 1700 to 2005: estimations from high-resolution satellite data and historical archives. Global Biogeochemical Cycles, 24, GB3003, doi:*10.1029/2009GB003687.*

Liu, J, W. Yang. 2013. Integrated assessment of payments for ecosystem services programs. *PNAS*, 110:16297-16298.

Lo, C.P. 2002. Urban Indicators of China from Radiance-Calibrated Digital DMSP/OLS nighttime Images. *Annals of the Association of American Geographers*, 92:225-240.

Lu, D., H. Tian, G. Zhou, H. Ge. 2008. Regional Mapping of Human Settlements in Southeastern China with Multisensor Remote Sensed Data. *Remote Sensing of Environment*, 112:3668-3679.

Mairs, K.A. 2007. Islands and human impact: under what circumstances do people put unsustainable demands on island envionments? Evidence from the North Atlantic. University of Edinburgh, PhD Thesis. Available from: http://www.nabohome.org/postgraduates/theses/kam/ (last access 30 August 2013).

Malthus, T.R. 2013. An essay on the principle of population (1798). Cosimo Classics, New York, NY.

Martinez-Zarzoso, I., A. Bengochea-Morancho, R. Morales-Lage. 2007. The impact of population on CO2 emissoins: evidence from European countries. *Environmental and Resource Econ*omics, 38:497-512.

Mather, A.S., C.L. Needle. 2000. The relationships of population and forest trends. The *Geographical Journal*, 166:2-13.

National Bureau of Statistics of China. 2002. China statistical yearbook 2002. Available from: http://www.stats.gov.cn/yearbook2001/indexC.htm (last accessed 20 January 2013).

National Bureau of Statistics of China. 2008. China statistical yearbook 2008. Available from: http://www.stats.gov.cn/tjsj/ndsj/2008/indexch.htm (last accessed accessed 20 January 2013).

Milesi, C., C.D. Elvidge, R.R. Nemani, S.W. Runnings. 2003. Assesing the impact of urban land development on net primary productivity in the southeastern United States. *Remote Sensing of Environment*, 86, 273-432.

Meyer, W.B. B.L. Turner II. 1992. Human population growth and global land-use/cover change. *Annual Review of Ecology and Systematics*. 23:39-61.

Min, S.K., X. Zhang, F.W. Zwiers, G.C. Hegerl. 2011. Human contribution to more-intense precipitation extremes. *Nature*, 470:378-381.

MODIS land team. 2011. Validation: Status for Land Cover/Dynamics (MCD12). Available from: http://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD12 (last accessed 31 October 2013).

MODIS land team. 2009. Validation Hierarchy. Available from: http://landval.gsfc.nasa.gov/ (last accessed 31 October 2013).

Moran, E.F. 1982. Human adaptability. Westview Press, Boulder, Colarado.

Numerical Terradynamic Simulation Group. 2010. The improved MOD17 dataset. Available from: http://www.ntsg.umt.edu/ (last accessed 14 January 2013).

Oak Ridge National Laboratory. 2010a. LandScan Documentation. Available from: http://www.ornl.gov/sci/landscan/landscan_documentation.shtml (accessed 23 January 2013).

Oak Ridge National Laboratory. 2010b. LandScan Frequently Asked Questions, Why can't I get the previous versions of the LandScan Global Population Datasets? http://www.ornl.gov/sci/landscan/landscan_faq.shtml#07. (accessed 23 January 2013).

Oda, T., S. Maksyutov. 2011. A very high-resolution (1 km × 1 km) global fossil fuel CO2 emission inventory derived using a point source database and satellite observations of nighttime lights. Atmospheric Chemistry and Physics, 11:543-556.

Openshaw, S. 1984. The modifiable areal unit problem. CATMOG 38. GeoBooks, Norwich, England.

Pattison, W.D. 1964. The four traditions of geography. Journal of Geography, 63:211-216.

Piao, S., J. Fang, P. Ciais, P. Peylin, Y. Huang, S. Sitch, T. Wang. 2009. The carbon balance of terrestrial ecosystems in China. Nature, 458:1009-1013.

Prince, S.D., S.J. Goward. 1995. Global primary production: a remote sensing approach. Journal of Biogeography, 22:316-336.

Qin, L., J. Hao, M. Hou, P. Meng. 2004. The effect of urban green system on the price of residential housing. Ecological Economics, S1:241-242 (in Chinese).

Raskin, P.D. 1995. Methods for estimating the population contribution to environmental change. Ecological Economics, 15:225-233.

Raupach, M.R., P. J. Rayner, M. Paget. 2010. Regional variations in spatial structure of nightlights, population density and fossil-fuel CO2 emissions, Energy Policy, 38:4756-4764.

Rees, E.E., 1992. Ecological footprints and appropriated carrying capacity: what urban economics leaves out. Environment and Urbanization, 4:121-130.

Roberts, J.T., P.E. Grimes. 1997. Carbon intensity and economic development 1962-91: a brief exploration of the environmental Kuznets curve. World Development, 25:191-198.

Running, S.W., T.R. Loveland, L.L. Pierce. 1994. A vegetation classification logic based on remote sensing for use in global scale biogeochemical models, *Ambio*, 23:77-81.

Running, S.W., R. Nemani, J.M. Glassy, P.E. Thornton. 1999. MODIS daily photosynthesis (PSN) and annual net primary production (NPP) product (MOD17): algorithm theoretical basis document. Available from: http://modis.gsfc.nasa.gov/data/atbd/atbd_mod16.pdf (last accessed 14 January 2013).

Running, S., M. Zhao. 2010. Note to users on use of MODIS GPP/NPP (MOD17) dataset. Available from: ftp://ftp.ntsg.umt.edu/pub/MODIS/Mirror/MOD17_Science_2010/ (last accessed 14 January 2014).

Sala, O.E., F.S. Chapin, J.J. Armesto, E. Berlow, J. Bloomfield, R. Dirzo, E. Huber-Sanwald, L.F. Huenneke, R.B. Jackson, A. Kinzig, R. Leemans, D.M. Lodge, H.A. Mooney, M. Oesterheld, N.L. Poff, M.T. Sykes, B.H. Walker, M. Walker, D.H. Wall. 2000. Biodiversity: global biodiversity scenarios for the year 2100. Science, 287:1770-1774.

Scepan, J. 1999. Thematic validation of high-resolution global land-cover data sets. Photogrammetric Engineering and Remote Sensing, 65:1051-1060.

Small, C., F. Pozzi, C.D. Elvidge. 2005. Spatial analysis of global urban extent from DMSP-OLS night lights. Remote Sensing of Environment. 96:288-291.

Stern, D.I. 2004. The rise and fall of the environmental Kuznets curve. World Development. 32:1419-1439.

Stern, P. C., O.R. Young, D. Druckman. 1992. Global environmental change: Understanding the human dimensions. National Academy Press, Washingto, D. C.

Stewart, J., W. Warntz. 1958. Physics of population distribution. Journal of Regional Science. 1:99-123.

Sutton, P.C., C.D. Elvidge, T. Ghosh. 2007. Estimation of gross domestic product at sub-national scales using nighttime satellite imagery. International Journal of Ecological Economics and Statistics, 8:5-21.

Sutton, P.C., A.R. Goetz, S. Tildes, C. Forster, T. Ghosh. 2010. Darkness on the edge of town: mapping urban and peri-urban Australia using nighttime satellite imagery. The Professional Geographer, 62:119-133.

Sutton, P.C., D. Roberts, C.D. Elvidge, K. Baugh. 2001. Census from Heaven: An estimate of the global human population using night-time satellite imagery, International Journal of Remote Sensing, 22:3061-3076.

Sutton, P., C. Roberts, C. Elvidge, H. Meij. 1997. A comparison of nighttime satellite imagery and population density for the continental united states. Photogrammetric Engineering and Remote Sensing, 63:1303-1313.

Tolba, M.K., O.A. El-Kholy (Eds). 1992. The world environment 1972-1992: two decades of challenge. Chapman & Hall, London.

Townsend, A., D.A. Bruce. 2010. The use of night-time lights satellite imagery as a measure of Australia's regional electricity consumption and population distribution. International Journal of Remote Sensing, 31:4459-4480.

Turner, B.L. 2002. Contested identities: human-environment geography and disciplinary implications in a restructuring academy. Annals of the *Association of American Geographers*, 92:52-74.

USGS. 2011a. Land processes distributed active archive center. Available from: https://lpdaac.usgs.gov/lpdaac/products (last accessed 14 January 2014).

USGS. 2011b. Land cover type yearly L3 global 500 m SIN grid. Available from: https://lpdaac.usgs.gov/lpdaac/products/modis_products_table/land_cover/yearly_l3_global_500_m/mcd12q1 (last accessed 23 January 2014).

Vitousek, P.M. H.A. Mooney, J. Lubchenco, J.M. Melillo. 1997. Human domination of earth's ecosystems. *Science*, 277:494-499.

Walker, B., C.S. Holling, S.R. Carpenter, A. Kinzig. 2004. Resilience, adaptability and transformability in social-ecological systems. Ecology and Society, 9(2):5. [online] URL: http://www.ecologyandsociety.org/vol9/iss2/art5/.

Walker, B., D. Salt. 2006. Resilience thinking: sustaining ecosystems and people in a changing world. Island Press, Washington, DC.

Ward, J.H. 1963. Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association*, 48:236-244.

Welch, R. 1980. Monitoring Urban Population and Energy Utilization Patterns from Satellite Data. *Remote Sensing of Environment*, 9:1-9.

Xu, J. 2011. China's new forests aren't as green as they seem. *Nature*, 477:371.

Xu, M., Y. Qi, P. Gong. 2000. China's new forest policy. *Science*, 289:2049-2050.

Xu, J., R. Yin, Z. Li, C. Liu, 2006. China's ecological rehabilitation: unprecedented effort, dramatic impacts, and requisite policies. *Ecological Economics*, 57:595-607.

York, R., E.A. Rosa, T. Dietz. 2003. Bridging environmental science with environmental policy: plasticity of population, affluence, and technology. *Social Science Quarterly*, 83:18-34.

York, R., E.A. Rosa, T. Dietz. 2003. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics*, 46:351-365.

Zhang, P. 2008. Revitalizing old industrial base of northeast China: Process, Policy and Challenge. *Chinese Geographic Science*, 18:109-118.

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

Zhao, N., N. Currit, E. Samson. 2011. Net primary production and gross domestic product in China derived from satellite imagery. *Ecological Economics*, 70:921-928.

Zhao, M., F.A. Heinsch, R.R. Nemani, S.W. Running. 2005. Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sensing of Environment*, 95:164-176.

Zhao, M., S.W. Running. 2010. Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. *Science*, 320:940-943.

Zhao, N., T. Ghosh, E. L. Samson. 2012. Mapping spatio-temporal changes of Chinese electric power consumption using night-time imagery. International Joural of Remote Sensing, 33:6304-6320.

Zhao, N., E. L. Samson. 2012. Estimation of virtual water contained in international trade products using nighttime imagery. International Journal of Applied Earth Observation and Geoinformation, 18:243-250.

Zhou, Y. 2002. The People's Republic of China national report on sustainable development. China Environmental Science Press, Beijing.