Dynamics of Land Use and Land Cover Changes in China

A thesis
submitted in partial fulfilment
of the requirements for the degree
of
Doctor of Philosophy in Economics
at
The University of Waikato
by

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2018

Abstract

A key contribution of environmental economics to policy making has been to provide empirical indicators of sustainable economic development. An economy is (weakly) sustainable if it saves more than the combined depreciation of its stocks of natural capital and produced capital. Thus, these indicators allow trade-offs where, for example, natural capital might be depreciated in order to build up other forms of capital, such as in the built environment or in the form of human capital. As an application of this general idea, this thesis focuses on the trade-offs between ecosystem services, provided by natural capital, and certain land use and land cover changes (LUCC) in China. With better understanding of these trade-offs, this thesis contributes to optimum management for sustaining ecosystem services and supporting socio-economic development.

The three case study areas are Hebei, Qinghai and Shandong provinces. I study trade-offs between landscape diversity and crop production, between grassland quality and livestock production, and between net primary productivity (NPP, a measure of the energy that enters ecosystems) and urbanization. After reviewing trade-off analyses of ecosystem services for sustainable land-use management (Chapter 2), the case studies are presented, with two chapters on Hebei, one on Qinghai, and three on Shandong. These chapters have econometric models for monitoring and assessing LUCC-induced ecosystem service changes, to enable quantitative analysis of the mechanisms available for policy-oriented optimum land-use management.

The case study areas each have different policy interventions that are designed to preserve or restore natural capital. For example, Hebei has ecological restoration

programs, such as the Green for Grain program, that are implemented in an attempt to conserve landscape diversity. Qinghai province has policies of enhancing ecological restoration for grassland conservation, in order to improve livestock production. Shandong province has enforced a prime cropland preservation policy in order to ensure high cropland productivity. Collectively, the case studies add to the literature on the use of sustainable land-use management strategies, while helping to illustrate some of the trade-offs that are central to environmental economics.

The results highlight issues created by conversion of cultivated land to urban use, in both Hebei and Shandong. In Qinghai province, grassland degradation, livestock production and farmers' income interact and affect LUCC and changes in ecosystem services. Restorative interventions, such as nature reserves, seem to have a positive effect on NPP, as a measure of ecosystem productivity. On the other hand, in Shandong province there is relatively low land productivity, as measured by the NPP, in regions covered by built-up area. While this thesis does not calculate a value for the produced capital and human capital in built-up areas, the reduction in the value of natural capital as a result of urbanization highlights the potential trade-offs and the need for careful measurement to help whether China is on a sustainable development path. In summary, the research in this thesis examines various land-use practices and management regimes for conserving ecosystem services, and contributes to the literature on how management of land use change and land cover change can influence ecosystem services in rapidly urbanizing China.

Acknowledgments

This work was financially supported by the National Natural Science Funds of China for a Distinguished Young Scholar (Grant No. 71225005), the research funds from the National Natural Science Foundation of China (Grant No. 71533004; Grant No. 41771568; Grant No. 41171434; Grant No. 7156113700), and the Key Project in the National Science & Technology Pillar Program of China (Grant No. 2013BAC03B00) and the National Key Programme for Developing Basic Science (Grant No. 2012CB955700) from the Ministry of Science and Technology of China, and the External Cooperation Program of Chinese Academy of Sciences (Grant No.Y4R0060Y4). I am grateful to Chief Supervisor Professor John Gibson, to Supervisors Professor Les Oxley and Dr Steven Lim, and to Professor Frank Scrimgeour for guidance. I am grateful to Maria Fitzgerald, Zhihui Li, Pei Wang, and Siqi Jia for their kind assistance.

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Chapter 1: Introduction

A key contribution of environmental economics to policy making has been to provide empirical indicators of sustainable economic development. The notion of 'Genuine Savings', which focuses on a nation's extended capital stock (i.e., natural capital, produced capital, and human capital), has become an indicator used by governments and agencies like the World Bank (Hanley, Dupuy, & McLaughlin, 2015). In particular, an economy is (weakly) sustainable if it saves more than the combined depreciation of its stocks of natural capital and produced capital (Pearce & Atkinson, 1993). Thus, these indicators allow trade-offs where, for example, natural capital might be depreciated in order to build up other forms of capital, such as the built environment or human capital.

In this thesis I focus on trade-offs between ecosystem services, which are provided by natural capital, and activities that cause land use and land cover changes (LUCC) in China. The trade-offs that I study are an application of the general idea of substitution between types of capital, which environmental economics has contributed as a way to empirically monitor sustainability. Of course, the literature on LUCC goes well beyond economics because it is one of the central themes of global change research (Lambin et al., 2001; Turner et al., 2007; Lambin et al., 2008). With the development of theory and methodology for studying the dynamics of land system change (Costanza et al., 2014; Sutton et al., 2016; Wunder et al., 2018) and the establishment of the Global Land Project (GLP, 2005), researchers have increasingly noted the close relationships among natural environmental evolution, terrestrial ecosystem processes, human production activities and the dynamics of land system change (Deng, 2011a; Deng et al. 2014a; Deng & Gibson, 2018a; Deng & Gibson, 2018b). In particular, the interaction between LUCC and ecosystems has brought growing attention to those relationships (Deng et al., 2014b; Deng et al., 2015a; Deng et al., 2015b).

This thesis aims to contribute to the optimum management for sustaining ecosystem services and supporting socio-economic development. It does so by focusing on three case study areas in China: Hebei province, Qinghai province, and Shandong province. These areas have different policy interventions that are designed to preserve or restore natural capital. For example, Hebei has ecological restoration programs, such as the Green for Grain program, implemented in an attempt to conserve landscape diversity. Qinghai province has policies to enhance ecological restoration for grassland conservation, in order to improve livestock production. Shandong has enforced a prime cropland preservation policy in order to ensure high cropland productivity. Collectively, the case studies add to the literature on the use of sustainable land-use management strategies, by looking at the impacts on the socio-economy from the dynamics of LUCC and by examining how policies or regulations adopted by central or regional governments in China may affect the trade-offs between natural capital, in terms of ecosystem services, and other forms of capital, such as the built environment.

Dynamics of land system changes and their effects on ecosystems are core issues studied by the International Geosphere-Biosphere Programme (IGBP) and the International Human Dimensions Programme (IHDP) (Costanza et al., 1997; GLP, 2005; Crossman et al., 2013; Deng et al., 2013; Li et al., 2013; White et al., 2016). It is worth recalling that an ecosystem is a dynamic intricate system of plant, animal and micro-organism communities and the non-living environment interacting as a functional unit, and that people are integral parts of ecosystems (MEA, 2003). Also important are the "ecosystem services", which are the direct and indirect benefits that people obtain from ecosystems (de Groot et al., 2002; Gascoigne et al., 2011). Amongst these ecosystem services are: provisioning services, such as providing food, water, timber and fiber; regulating services, such as the regulation of climate, flood, disease, wastes and water quality; cultural services, such as offering recreational, aesthetic and spiritual benefits; and supporting services, such as soil formation, photosynthesis and nutrient cycling.

There can be tension between socio-economic development and the provision of ecosystem services. For example, the UK National Ecosystem Assessment reported that about 30% of ecosystem services were currently declining and many others were in a reduced or degraded state. The globalization of economies, flows of people, growing population, intensification and diversification of land use and advances in technology are all crucial driving forces for the decline of ecosystem services (Lambin et al., 2001; Farber et al., 2002; Rindfuss et al., 2004; Olivia et al., 2011; van Oudenhoven et al., 2012). On the other hand, the urgent demand of conserving ecosystem services for sustainable development places great pressure on reasonable land resource allocation (Wu et al., 2013). Therefore, international organizations, individual countries and scholars are increasingly aware of the environmental impacts of LUCC (de Groot et al., 2006; Salzman et al., 2018).

Land use is a key human activity, which is able to foster socio-economic development, and alter structures and processes in the environment through the exploitation of natural resources (Helming et al., 2008). People everywhere depend on ecosystems to provide necessary services for their livelihoods and their well-being through various ecosystem services, which directly or indirectly sustain the quality of human life. Meanwhile, ecosystems are increasingly subject to multiple human uses and pressures which are projected to compromise their ability to deliver ecosystem services necessary to support mankind; while LUCC also exerts certain effects on those various ecosystem services over space and time (Deng et al., 2011b). This trade-off can especially be seen in agricultural ecosystems and grassland ecosystems. From the perspective of agricultural ecosystem services, these would definitely be weakened if the cultivated land was degenerated or occupied, which would result in the loss of food production. A similar situation applies to grassland ecosystem services (Deng et al., 2013).

This thesis focuses on the trade-offs between ecosystem services, and certain land use and land cover changes (LUCC) in China. In terms of the broader notion of weak sustainability from environmental economics that is noted above, the trade-offs that I examine in this thesis are, broadly speaking, between natural capital and produced capital, particularly in the form of built urban environment. With better understanding of these trade-offs, and of the effect of land-use practices and management for conserving ecosystem services, it is hoped that the research in this thesis will contribute to optimum management for sustaining ecosystem services while balancing the need to use some natural capital to support socio-economic development.

The remainder of the thesis is constructed as follows. Chapter 2 provides a review of trade-off analyses of ecosystem services for sustainable land-use management. Chapter 3 explores the relationship between landscape diversity and crop production through a case study in Hebei province. In Chapter 4, sustainable land use management for improving regional eco-efficiency is studied, again for Hebei. Chapter 5 quantitatively measures the interaction between net primary productivity and livestock production in Qinghai province. In the following three chapters - Chapter 6 to 8, studies on the dynamics of land use and land cover changes and their impacts on ecosystem services for Shandong province are reported. Chapter 6 analyzes the managements of trade-offs between the conversion of cultivated land and changes in land productivity. In Chapter 7 I examine a specific type of trade-off between natural and produced capital, which is the question of whether expressways consume more of the agricultural production base. In Chapter 8, there is an exploration of how to improve eco-efficiency for the sustainable agricultural production. The final chapter concludes and discusses the limitation of the research included in this thesis. The following paragraphs are a relatively detailed introduction to each chapter.

The focus of chapter 2 is on reviewing analysis tools and approaches to trade-offs in ecology, economics and other fields. The objective of this chapter is to explore the most frequent ecosystem services trade-offs associated with land-use practices and management, and to compare techniques that measure trade-offs among ecosystem services across spatial and temporal scale. Major barriers to effective resource planning and management that contribute to ecosystem service trade-offs at different temporal and spatial scale include stakeholders' preferences and the degree of irreversibility. The analytical tools and approaches that have been developed and applied to management decisions include the assessments that explicitly link spatial information on service supply to conduct correlation or cluster analysis, the integrated modeling framework for the systemic assessment, and approaches based on the multi-criteria decision theory and economic production theory. Evaluation of trade-offs is complex due to the multiple dimensions, interactions, variations and uncertainties with different physical units across time and space. Quantifying the non-linear dynamics of trade-offs between ecosystem services in the social-ecological systems that are driven by both biophysical drivers and management decisions remains a big challenge for sustainable land-use management. A version of Chapter 2 of this thesis has been published in the *Journal of Geographical Sciences* (Deng, Li, & Gibson, 2016).

Chapter 3 explores the relationship between landscape diversity and crop production for the case of Hebei province. Quantitative analysis shows the ratio of cultivated land tends to decrease with the increase in landscape diversity (as revealed using Shannon's Index). The apparent contribution of landscape diversity to crop production could be regarded as an ecological effect supplied by landscape, although the magnitude of this effect is small. Thus, policies to pursue crop production might take the advantages of landscape diversity into account, along with the more typical agricultural inputs such as agricultural machinery, fertilizer and electricity, and the construction of infrastructure, as feasible and practical ways for advancing crop production. A version of Chapter 3 of this thesis has been published in t*he Journal of Cleaner Production* (Deng, Gibson, & Wang, 2017a).

Chapter 4 explores the sustainable land use management for improving regional eco-efficiency in the case study area of Hebei province, where the issue of conversion of cultivated land, which is expected to impact on crop yields and ecosystem services, has been brought to prominence by recent urban expansion. In this chapter, I first explore the relationship between land use conversion, the ratio of cultivated land to total land, and crop production using scatter plots. Next, an econometric analysis was performed to examine the relationship between land use conversion and changes in cultivated land. Subsequently, quantitative analysis was performed to assess the regional eco-efficiency and ecological performance of prefectural cities in Hebei province. Chapter 4 indicates that crop production is positively related to the ratio of cultivated land to total land, with a nonlinear relationship. The results for the distribution of eco-efficiency show that the excessive consumption of ecological resources has not occurred during the urbanization process in Hebei province. A version of Chapter 4 of this thesis has been published in *Annals of Operations Research* (Deng & Gibson, 2018a).

In Chapter 5, the focus is placed on quantitative measurement of the interaction between net primary productivity (NPP), which provides one way to measure the health of an ecosystem, and livestock production in Qinghai province. The case study reveals that there is a positive relationship between the value of livestock production and NPP. The results indicate that NPP in a county-level region with nature reserves was about 6% higher than in equivalent regions without nature reserves when all other factors are kept the same (with the effect statistically significant at the 99% level). Thus, there may be a small indirect effect of nature reserves on the value of livestock production via NPP. Given that higher grazing density negatively affects NPP, establishing appropriate grazing density as a first priority, and then establishing natural reserves as a second one is practical actions to sustain livestock farming in this region. Sets of effective measures for sustainable resource management have also been put forward in this chapter. A version of Chapter 5 of this thesis has been published in the *Journal of Cleaner Production* (Deng, Gibson, & Wang, 2017b).

In Chapters 6 to 8 the thesis examines Shandong province, which is China's largest agricultural exporter. The first case study is of management of trade-offs between land productivity and the conversion of cultivated land to non-agricultural (industrial and urban) use. I use the Estimation System of Land Productivity (ESLP) approach to calculate potential productivity for each 1km × 1km grid cell, where ESLP is based on agro-ecological zones through considering common characters, inclusive of climate conditions, soil properties and other geographic features affecting crop growth. This measure takes account of photosynthetic productivity, light and temperature productivity, climatic productivity, soil productivity, and land productivity. The land productivity is lower in the regions of the province where cultivated land was converted to other uses over the 1985-2010 study period. A version of Chapter 6 of this thesis has been published in the *Journal of Cleaner Production* (Deng, Gibson, & Wang, 2017c).

In Chapter 7, I look at the potential trade-off between one form of built capital – transport infrastructure, and specifically, expressways, and one form of natural capital, in the form of agricultural land that is suitable for cultivation. Prior research elsewhere in China (Jiangxi) claims that roads are more like "pressure values" in the sense that they release pressure on one form of natural capital – forests – by enabling the population to switch to less forest-demanding activities, rather than acting like “pressure cookers” as would occur if roads increase the rate of forest loss (Deng et al, 2011c). A related question is examined in this chapter, by testing whether the existence of a nearby expressway in 2005 (where nearby is in terms of whether it enters the watershed that a land pixel is located in) affected the level of cultivated land in 2010, and the rate of change in cultivated land from 2005 to 2010. The main strategy in this analysis is to start by looking at the simple relationship between the presence of expressways and cultivated land loss, then adding 24 additional covariates to measure the net effect of expressways on cultivated land changes, and finally using matching methods to at least in part control for observed and unobserved differences between pixels that have different degrees of access to expressways in order to obtain unbiased treatment effects estimates. The analysis suggests that that there is no adverse impact of roads on causing cultivated land in Shandong province to decline. Given that roads are important to socio-economic development strategies, and that roads are a form of produced capital, the lack of trade-off implies that in this particular instance China is not depleting natural capital faster than it is generating produced capital (although other forms of natural capital may be affected by road building). A version of Chapter 7 of this thesis has been published in *Computational Economics* (Deng, Gibson, & Jia, 2017d).

In Chapter 8 I consider another way to examine trade-offs related to urbanization and land productivity, using Stochastic Frontier Analysis (SFA). In this chapter I also introduce two additional indicators, the Ecological Performance Indicator (EPI) and the Eco-efficiency (EE) indicator. The EPI is defined as the ratio of the distance function values obtained from the production function that incorporates the ecological inputs to those from the production function without ecological inputs. The EE is defined as the ratio of minimum feasible ecological input use to observed ecological input use, conditional on the observed levels of the other inputs and outputs (Reinhard et al., 1999). The eco-efficiency results for the ratio of built-up area within Shandong imply presence of a trade-off between urbanization and land productivity. The trade-offs between land productivity and cropping returns, and between urbanization and cropping returns can also be embodied by net primary production

(NPP). This means that the EE can be calculated in another way to explain different trade-offs based on the ESLP. In line with the findings in Chapter 6, land productivity appears to be unevenly distributed in Shandong province, with relatively lower values in regions covered by built-up area. The regional eco-efficiency in Shandong was mostly over 0.9, except for prefectures located far from the main political or economic centers. A version of Chapter 8 of this thesis has been published in *Technological Forecasting and Social Change* (Deng & Gibson, 2018b).

To summarize the thesis as a whole, some of the driving forces for, and impacts of, land use and land cover change in China, and related ecosystem service changes, are analyzed. To make the study manageable, I look at cases in three regions—Hebei, Qinghai and Shandong provinces—to specifically analyze particular trade-offs where changes in ecosystem services are likely to be caused by the local LUCC. In Hebei province, as in much of coastal China, urban expansion has highlighted issues of cultivated land conversion. Crop yield is influenced by landscape diversity and by the services provided by ecosystems. At the same time, agricultural income generated by crop yield is a large component of farmers' income. Therefore, in Hebei province, landscape diversity loss caused by the rapid urbanization is threatening the food production, which also influences the farmers' income.

In Qinghai province, grassland degradation, livestock production and farmers' income interact, as part of the land use and land cover change. Natural grasslands are on the decline on a global scale and this loss of ecosystem services is also apparent in Qinghai. More optimistically, my research indicates that there is a weak positive effect on net primary productivity (as a measure of the health of ecosystems) in the county-level regions that have nature reserves and so conservation efforts may help to reduce the decline in productivity due to grassland degradation. Higher grazing density negatively affects net primary productivity, so promoting appropriate grazing density regimes and creating natural reserves are practical actions to sustain livestock farming.

In Shandong province, there exists interaction between urbanization, crop production and conservation of forestry and grassland covers. Urbanization has highlighted the issue of built-up land expansion with the decreasing area of cultivated land and forest, which could affect the land productivity measured by the net primary productivity (NPP) of terrestrial ecosystems. Based on the estimation of effects on land productivity, and on the analyses of eco-efficiency of agricultural production, the results indicated existence of trade-offs between agricultural production and urbanization. Consequently, it is necessary to adjust the agricultural technological measures in use, according to specific local conditions, in order to improve land productivity measured by the NPP, if there is to be any attempt to make up for the effects of urbanization on the sustainable agricultural development in Shandong province.

To sum up, this thesis focuses on the trade-offs between ecosystem services, provided by natural capital, and certain land use and land cover changes (LUCC) in China. With better understanding of these trade-offs in the three case study areas (Hebei, Qinghai and Shandong provinces), this thesis contributes to optimum management for sustaining ecosystem services and supporting socio-economic development. The case study areas each have different policy interventions that are designed to preserve or restore natural capital, such as the Green for Grain program for conserving landscape diversity in Hebei, the enhancement of ecological restoration for grassland conservation in Qinghai and the enforcement of prime cropland preservation for ensuring high cropland productivity in Shandong, respectively. Other areas in China, and indeed in other countries that are undergoing some of the transformations seen so dramatically in China, have other policies for preserving or restoring natural capital. It is possible that some of the techniques drawn upon in this thesis could be applied in these other settings. In this manner, this thesis aims to add to the existing literature on the use of sustainable land-use management strategies in China, while more broadly helping to illustrate some of the trade-offs that are central to environmental economics.

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Chapter 2: A Review on Trade-off Analyses of Ecosystem Services for Sustainable Land-use Management

This paper has been published in the *Journal of Geographical Sciences* 26, 953–968.

Abstract

Ecosystem services are substantial elements for human society. The central challenge to meet the human needs from ecosystems while sustain the Earth's life support systems makes it urgent to enhance efficient natural resource management for sustainable ecological and socioeconomic development. Trade-off analysis of ecosystem service can help to identify optimal decision points to balance the costs and benefits of the diverse human uses of ecosystems. In this case, the aim of this paper is to present key insights into ecosystem services trade-off analysis at different scales from a land-use perspective, by comprehensively reviewing the trade-offs analysis tools and approaches that addressed in ecology, economics and other fields. The review will significantly contribute to future research on a trade-off analysis to avoid inferior management options and offer a win-win solution based on comprehensive and efficient planning for interacting multiple ecosystem services.

Keywords: ecosystem services; trade-offs; land-use management; scale; integrated modeling; multi-criteria analysis; efficiency frontier

1 Introduction

Ecosystem services, which are broadly defined and extensively identified as the benefits obtained either directly or indirectly from ecosystems, are of great significance to human well-beings. Ecosystem services flow into human society and provide fundamental life-support for human civilization. From clean water supply to erosion control, from food provision to climate regulation, from recreation to scenic beauty, all humans' life needed are provided by Earth's ecosystems (Daily et al., 1997). Since the concept of ecological system being put forward by Tansley (1935), the study of ecological system has gradually become a scientific framework, and has been further strengthened since the end of 20th century. With varying attentions and perspectives, from the biological basis to economic concerns, the concepts and evaluations of ecosystem services have evolved through various research projects (Costanza et al., 1998; MEA, 2005a; TEEB, 2010; de Groot et al., 2010a). Most of these research efforts were concentrated on the evaluation and mapping of the biophysical or economic values of ecosystem services at different scales, and the impact mechanisms of human activities and natural changes (Li et al., 2013; Deng et al., 2013), shedding lights on the identification of the benefits that human society receive from the nature and providing information for decision making. Clarifying the current situation of ecosystem services is a prerequisite for further analysis and solutions identification.

In real word contexts, as a kind of human civilization, the land-use management activities profoundly altered the ecosystems. Currently, there is a trend that an ever-large amount of ecosystem goods and services have greatly benefited humans. However, the capacity of global ecosystems for sustainable development is simultaneously degrading, leading to unintended environmental consequences that will potentially jeopardize the future land-use options (World Bank, 2008). Confronting the global challenges that land use changes substantially affect and alter ecosystem services, trade-off analysis on ecosystem services associated with decisions between land use alternatives has become the focus of land-use management (Ryffel et al., 2014). In order to avoid unwanted and possibly irreversible effects of land-use change, sustainable land-use management should assess and manage inherent trade-offs between the site-specific immediate human needs and maintaining the long-term ecosystem services provisions. Trade-offs will arise if particular land-use management decisions are made, which will result in changes of the types, magnitudes, and relative mix of services provided by ecosystems. In addition, since each ecosystem service is not independent, but instead exhibits complex interactions, which will further lead to different environmental or socioeconomic outcomes related to different individuals or groups (Rodríguez et al., 2006). Over time, in spite of the great progress and success in the assessment of the ecosystem services trade-offs, the practical application in land-use management decision is limited (Daily et al., 2009). The underlying reason is that most studies have been focused on one or a few services without considering the interdependence and highly non-linear relationships among the ecosystem services (Ring et al., 2010). Land-use management and decision makings with focus only on one type of ecosystem services without considering others will result in policy failure. In this sense, the understanding and knowledge about inter-linkages and potential trade-offs among different ecosystem services should be deepened and expanded to explore new insights in innovations related to institutions and governance (Elmqvist et al., 2013).

Although trade-offs analysis has become a hot topic in ecosystem services researches, few studies were conducted across disciplines. This study aims to explore the most frequent ecosystem services trade-offs associated with land-use practices and management, and compare techniques that measure trade-offs among ecosystem services across spatial and temporal scale based on comprehensive revisits to relevant research. Firstly, we summarize the definitions and characteristics of ecosystem services trade-offs, then recognize trade-offs among ecosystem services at different scales. Subsequently, we elaborate the technics in different disciplines that are applied to investigate and measure the trade-offs for decision makings. Based on the review works, it will provide a comprehensive framework for future researches on ecosystem services trade-offs, which is critical to decision making for sustainable land-use management.

2 Trade-offs of ecosystem services

2.1 Definitions of trade-offs

Trade-off is a fundamental concept in economics, while being especially applied in an evolutionary context (Garland, 2014). In economic context, a trade-off is commonly expressed as the opportunity cost which is the preferred alternative when taking an economic decision, deriving from the idea that resources are scare, which means to obtain more of one scarce resource, an individual or group collectively must give up some amount of another scarce good (de Groot et al., 2010b). In the ecosystem services context, the definition of trade-offs is mainly derived from the Millennium Ecosystem Assessment (MEA), which is defined as management choices that intentionally change the services provided by ecosystems (MEA, 2005b). In addition, The Economics of Ecosystems and Biodiversity (TEEB) described the trade-offs of ecosystem services as the way in which one ecosystem service responds to the changes in another service (TEEB, 2010). There are also some refined definitions of trade-offs, indicating the interactions among ecosystem services that result in the increasing provision of one ecosystem service at the cost of reducing other services (Haase et al., 2012). Generally, trade-offs of ecosystem services occur when human interventions enhance the output of an ecosystem services while negatively affect the provision of other services (de Groot et al., 2010b; Elmqvist et al., 2013).

2.2 Recognitions of trade-offs

Over time, socioeconomic development and human well-beings are heavily relying on the provision of natural ecosystem services. On one hand, some of the ecosystem services functions are treated with priority and are intentionally modified due to their critical and important roles in the delivery of goods and services to support the human society, on the other hand, however, some of other services are ignored and damaged (Deng et al., 2011; Seppelt et al., 2013). Ecosystem is of extreme complexity and of great spatial and temporal variation in different ecological context. Identifying the specific trade-offs among different types of ecosystem services at different scales would help to convey information in a clear manner and provide decision-making framework about ecosystem services across geographic, ecological and socioeconomic dimensions (Ruhl et al., 2007; Tallis et al., 2008). In addition, it can also facilitate scientists and policy makers a better understanding of the potential consequences of unbalanced treatment of the ecosystem services functions in the process of land-use management (Haase et al., 2012).

2.2.1 Trade-offs in ecosystems

Considering the complexity and interactions of the ecosystem services for the human society, researches on the trade-off analysis between the provisioning and regulating services and the investigation on the relationship of multiple ecosystem services and biodiversity are provoking. Agroecosystem is a good example in this case (Bennett and Balvanera, 2007; Nelson et al., 2008; Ring et al., 2010; TEEB, 2010; Elmqvist et al., 2013).

Agricultural land covers about 35% of the Earth's terrestrial surface (MA, 2005d), providing a series of provisioning (e.g., food, wood, and water), regulating (e.g., climate, carbon, and erosion), supporting (e.g., pollination, biodiversity/habitat), and cultural (e.g., recreation and education) services (Power, 2010). Over the past decades, humans changed the Earth's surface extensively for agriculture activities to meet the increasingly demand for provisioning services, which severely affect the current and future generation of many regulating services and biodiversity (Bennett and Balvanera, 2007). For agroecosystem, the typical problem is that agricultural intensification and centralization related to the provisioning ecosystem services for higher macro-economic output usually reduce or damage the other ecosystem services related to the ecosystem regulation and maintenance, as well as cultural services (Kirchner et al., 2015).

There are several studies explicitly analyzed the possible trade-offs among various ecosystem services for agroecosystems. Specific trade-offs have been identified, such as the interactions between agricultural production and regulating services, e.g. sediment yield (Swallow et al., 2009) and carbon sequestration (Crossman et al., 2011). Biodiversity conservation is also commonly viewed as trade-off with agricultural production. Biodiversity is not equated to a specific ecosystem service or bundle. Most studies tried to investigate the trade-offs between biodiversity conservation and bundles of ecosystem services in agroecosystems. Barraquand and Martinet (2011) analyzed the trade-offs between agricultural production and biological conservation at the landscape scale. Mason et al. (2012) revealed that the investment directed into mitigating the impacts of agriculture on ecosystem services rather than biodiversity restoration would result in lower biodiversity. One research examined the potential trade-offs between agricultural production and biodiversity benefits, revealed that the benefit gained from an increase in biodiversity would outweigh the loss of returns from agricultural production (Dymond et al., 2012).

Little evidence and quantitative analysis on the interactions and linkages among ecosystem services bundles had been recognized as a major research gap regarding ecosystem services(Carpenter et al., 2009) and resulted in mixed conclusions (Bohensky et al., 2006). Recently, in order to provide implications for sustainable land-use management, researches on the types of interactions and the corresponding feedbacks among different ecosystem services are stimulated. For example, Brauman et al. (2007) revealed that water quality regulation services with other services, such as habit for biodiversity and climate regulation, can be co-delivered by vegetation, requiring the analysis of trade-offs among multiple services (Butler et al., 2013). It has been a major research priority to consider biodiversity conservation bundles and ecosystem services bundles during payment implementation (Wendland et al., 2010). In addition, some studies have revealed that when taking multiple services into consideration, the outcomes with maximized net gains of land-use management will be achieved more efficiently (Crossman and Bryan, 2009).

Intensive land-use change and management have been recognized as the major drivers that alter ecosystem services provision from agroecosystems (Sheng et al., 2011; Bryan, 2013). Wang et al. (2015) quantified the multiple ecosystem services in the Sanjiang Plain of China and concluded that the significant loss of ecosystem carbon stocks and natural habitats with grown food production was due to the extensive land conversion from natural wetlands to cultivated land. Similarly, Haines-Yong et al. (2012) confirmed a trade-off between the provisioning services ("crop-based production") and regulating services ("habitat diversity"). Also, during the process of ecological restoration, which converted he agricultural land back to natural ecosystems, trade-offs can be found among different ecosystem services, such as trade-off between biodiversity and salinity mitigation (Maron and Cockfield, 2008), between carbon sequestration and species conservation (Nelson et al., 2008), food production (Paterson and Bryan, 2012), and water supply (Chisholm, 2010). While, as humans play a critical role in managing the agroecosystem, political practices, socioeconomic incentives and technological progresses are likely to influence the quantity and quality of ecosystem services, which will further affect the direction of trade-offs (Nelson et al., 2009). Compared to the results of the research conducted by Wang et al. (2015), the study in the Loess Plateau of China by Lü et al. (2012) showed an opposite result, indicating synergy between food production and ecosystem carbon stocks with the conversions of farmland to woodland and grassland, which can be contributed to agricultural technological growth, improvement of agricultural management and production efficiency. Nelson et al. (2009) also identified that policy interventions could modify the negative trade-offs between commodity production and other ecosystem services and biodiversity conversions. Maes et al. (2012) confirmed that there exist trade-offs among provisioning ecosystem services, regulation services and biodiversity conservation from agroecosystems, while he emphasized that trade-offs can be mitigated through specific management measures, such as increase cropping diversities and plant buffer strips. In this sense, trade-offs between agricultural production and other ecosystem services are not inevitable. Analysis on yields from agroecosystems indicated that with efforts on practice to conserve ecosystem services through measures, such as conservation tillage, crop diversification and biological control, ecosystem services trade-offs would be mitigated, with even improvements in yields (Badgley et al., 2007). These analyses suggest trade-off analysis should be incorporated into the land-use management decision making process, which can make a 'win-win' situation possible, where provisioning services are maintained and enhanced whilst other ecosystem services are supported.

2.2.2 Trade-offs of ecosystem services at different scales

The recognition of trade-offs should be conducted at different scales. It is commonly acknowledged that ecosystem services trade-offs occur at different spatial and temporal scale (Rodríguez et al., 2006; Power, 2010) and vary across both space and time (Holland et al., 2011), which increase more uncertainty to be managed. In addition, trade-off analysis from other perspectives are also proposed to be of great significance to land-use management and decision making, such as trade-offs among different stakeholders (Ring et al., 2010) and the reversibility of ecosystem services (Rodríguez et al., 2006).

Trade-offs at time scale. Trade-offs at time scale arises when policy-makers make choices between current and future benefits. Identifying such trade-offs can help policy-makers understand that management decisions should consider the long-term effects of preferring the short-term provision of one ecosystem services at the expense of future use of this same ecosystem service or other services (Rodríguez et al., 2006). Rodríguez et al. (2005) elaborated a broad topic about the temporal trade-offs during decision makings, which revealed that there would be many important trade-offs between current use of nonrenewable resources and their future use. It was pointed out that that slowly natural processes, such as soil formation, groundwater supply and genetic diversity generation that underlay supporting services, were always being ignored since that they were difficult to be detected and quantified, which would seriously damage the long-run sustainable provision of ecosystem services. For example, the collective activities of farmers to replace the original woody vegetation with pasture and corps for the short-term increase in agricultural production led to the water table being moved toward the surface, bring salt upward through the soil, which finally result in land salinization in the long-term future (Greiner and Cacho, 2001; Briggs and Taws, 2003). During the natural processes, there exist a great deal of uncertainties associated with large time lags in the feedback between changes in ecosystem process and other factors, posing much more difficulties in forecasting eventual outcomes and identifying the critical thresholds of ecosystem services (Holling, 1973; Rockström et al., 2009). For a balanced feedback loop during the resource management, the ability to recognize the trade-offs between current and future desirable states and 'time preferences' for ecosystem services becomes important and critical to make better decisions on land-use management (van den Belt et al., 2013).

Trade-offs at spatial scale. Spatial trade-offs could be simply recognized as benefits here while cost there (Ring et al., 2010), it occurs spatially between different landscapes, ecosystems, communities and even countries. For example, the improvement in water productivity with more agricultural inputs in the upstream will consequentially impact the water quality regulation services and incur costs in the downstream (Pattanayak, 2004). Such trade-offs have been illustrated specifically in the agricultural production in the USA, where the highly intensive agriculture relied greatly on artificial fertilization and finally led to massive negative impacts on the fisheries in the Gulf of Mexico (Tilman et al., 2002; Cumming, 2005). Spatial trade-offs are also well-known in economics, the environmental economists use spatial externality to indicate the positive or negative effects of land-use management decisions on ecosystem services in extended areas than those ecosystem services of where the decisions incurred that cost or benefit (Tietenberg, 1988). For example, the extensive division of water from rivers for drinking or agriculture irrigation in the upper regions will trigger water scarcity in the regions lower down the watershed (Falkenmark, 2003), while the local cost to conserve the biodiversity will benefit the global (Ring, 2008). The need to account for the spatial effects outside traditional geopolitical boundaries when facing ecosystem services decisions has been recognized by many managers, while practically it was rare that managers would give consideration to large-scale benefit at the cost of local wellbeing. It implies that incentives are needed to encourage managers think broadly to integrate experiences of small-scale ‘‘win-win’’ solutions to solve large-scale and macro problems (Rodríguez et al., 2005).

Trade-offs among stakeholders. Ecosystem services trade-offs among stakeholders means some stakeholders win while other lose, that is, one benefit from a particular ecosystem service at the cost of other individuals (Rodríguez et al., 2006). The UK National Ecosystem Assessment (UKNEA) defined such trade-offs as two outcomes: one is that the quality or quantity of an ecosystem service being utilized by one stakeholder was reduced or deteriorated due to others' utilization of that or other ecosystem services; the other one is that the utilization of ecosystem services by one stakeholder would lead to the decline of others' wellbeing (UKNEA, 2011). Different stakeholders derive wellbeing from a variety of ecosystem services based on their choices of development and management of particular services, which are strongly influenced by lots of factors, such as their beliefs, preferences, and experiences over time (McShane et al., 2011). Trade-offs occur among different ecosystem services due to inherent biophysical constraints in time and over space, then the divergent preferences on ecosystem services of different stakeholders will trigger conflicts (Martín-López et al., 2012). For instance, land use activities in terrestrial ecosystems impact the water regulation services through hydrological processes, then it will arise the conflicts among a range of associated stakeholders that depend on terrestrial ecosystems and aquatic ecosystems (Silvestri and Kershaw, 2010). In this case, reconciling stakeholders' divergent preferences over ecosystem services with explicit recognition of the nature of biophysically based trade-offs is crucial to identify sustainable solutions (King et al., 2015). With stakeholders' preferences being valued and added into the trade-off analysis, it makes the values intrinsic to ecosystem services (Brauman et al., 2007), and most researchers recently thought that the values as sources of conflicts that should be separated with biophysical constraints (Mouchet et al., 2014; Yahdjian et al., 2015). Especially, Cavender-Bares et al. (2015) presented a sustainability framework that characterizes ecosystem service trade-offs in terms of two dimensions of ecosystem service conflicts: biophysical constraints, and divergent preferences and values of stakeholders. The framework enables the identification of driving factors of and direct visualization of trade-offs due to stakeholders' preferences at spatial or temporal scale (Cavender-Bares et al., 2015). King et al. (2015) further evaluated the utility of the framework for ecosystem services trade-off analysis with critical insights to clarify conflicts among stakeholders under different scenarios.

Trade-offs in terms of reversibility. Reversibility of ecosystem services means the possibility of disturbed ecosystem service being reversed back to its original state once the perturbation ceased (Rodríguez et al., 2005). Trade-offs effects can be felt over time and spatial scale, indeed, some trade-offs may be irreversible. Regarding that the ecosystem services may be changed irreversibly, the importance of thresholds has been highlighted in the Millennium Ecosystem Assessment (MA, 2005c). When a system crosses a threshold due to persistent or strong environmental or socio-economic drivers, it will trigger great costs to society due to the irreversible loss of critical natural capital (Farley, 2012). Ring et al. (2010) interpreted the thresholds as resilience, which stands for a system's ability to adapt to the perturbations and stay persistent without changes. Further, considering the thresholds, they put forward four types of non-linear dynamics in ecosystems. It includes: a system with 'no-threshold effect', where it is revisable no matter how the changes in the controlling variables; a system with 'threshold, no alternate attractors', where slight change in controlling variable will significantly alter the system while it is still revisable if changes pass the threshold; and a system with 'threshold, alternate stable state', where it may be irreversible with large changes in the controlling variables that pass the thresholds; and a system with 'irreversible threshold change', where the changes shall not exceed thresholds to avoid irreversible situations (Ring et al., 2010). The existing of thresholds and relevant irreversible dynamic changes may curse various problems for sustainable development of socioecological systems, e.g. application of fertilizer in agricultural production that exceeds the thresholds will pose negative impacts on water quality. While with recognition of the thresholds, such as that precise agriculture will achieve greater crop yield with same inputs, while with less damages to ecosystems (Cavender-Bares et al., 2015). Thus, being aware of how far-reaching the effects, whether the effects is reversible, and how quickly can it be reversed, managers can make decisions appropriately to mitigate any negative effects and achieve "win-win" solutions (Rodríguez et al., 2005).

In dealing with the trade-offs in the context of ecosystem services, there exist multiple interactions and linkages among services at different scales that should be taken into consideration at first place, such as processes and management interventions of different stakeholders across various spatial and temporal scale. In addition, variations in the thresholds of ecosystems are closely related with the reversibility, making it is difficult to estimate the ecological issues. Facing the above issues, managers should complement their decisions with trade-offs at multiple spatial, temporal and stakeholder scale into consideration, with recognition of the threshold to minimize the negative effects of trade-offs.

3. Quantification analysis of trade-offs

Management of the complex social-ecological system requires tools to depict trade-offs among ecosystem services. As reviewed above, the major barriers to effective management contribute to that services trade-offs differ across time and space, and that different group of stakeholders possess different preferences for services. To deal with the barriers, researches in different disciplines have applied a variety of tools and approaches to quantitatively analyze these ecosystem service trade-offs. For a comprehensive knowledge of tools and approaches, we conduct a review of how ecosystem services trade-offs being analyzed at different scale from various perspectives.

3.1 Mapping trade-offs via correlation analysis and cluster analysis

GIS-based spatial mapping analysis are frequently applied to provide detailed information on ecosystem services indicators and further assist begin to understand and visualize potential trade-offs (Kirchner et al., 2015). For example, Maes et al. (2012) confirmed trade-offs between multiple ecosystem services and biodiversity with GIS-based spatial mapping and correlation analysis in Europe. Similarly, Maskell et al. (2013) identified intensive trade-offs between soil carbon storage and above-ground net primary production based on maps and pairwise correlations. The two examples above just investigated the trade-offs among multiple ecosystem services across space with no changes at time scale. While in practical terms, trade-offs are usually identified in response to land-use changes under particular management actions and measures or designed scenarios over time. Jiang et al. (2013) mapped changes in agricultural production, carbon storage and biodiversity, and further conducted spatial statistical analysis on the trade-offs at landscape scale in the UK during 1930-2000. In addition, trade-off analysis is mostly conducted from the perspective of biophysical supply side, while studies are scarcely conducted to assess and map ecosystem services trade-offs from the aspects of social demand side. To address both biophysical supply and social demand sides, Castro et al. (2014) identified ecosystem services trade-offs based on correlation analysis, both on the supply and the social demand sides, and analyzed spatial mismatches among the ecosystem services on biophysical, socio-cultural and economic dimensions within a spatial unit.

Correlation analysis on the trade-offs based on mapping simply identifies the interactions between pairs of ecosystem services, while trade-offs and synergies are more generally found within the bundles of services, indicating that a more integrated perspective on bundles of services is required for trade-off analysis among ecosystem services (Haines-Young et al., 2012). Regarding the interactions among ecosystem services bundles, cluster analysis was mostly applied. Cluster analysis based on mapping is a powerful tool to identify ecosystem service bundle types and analyze ecosystem service trade-offs and synergies (Raudsepp-Hearne et al., 2010). Especially, it is a more appropriate way when prior knowledge about what the trade-offs involve is not available (Medcalf et al., 2014). Raudsepp-Hearne et al. (2010) applied the concept of ecosystem service bundles to analyze interactions among ecosystem services, in which cluster analysis determined the provision of all 12 ecosystem services grouped the 137 municipalities into six data clusters. Also, Haines-Young et al (2012) explored the trade-offs between the selected services with cluster analysis, in which seven spatially explicit clusters were distinguished with distinct evolutionary trajectories of ecosystem services.

GIS-based spatial mapping with accompanied correlation or cluster analysis on the interactions among ecosystem services is a useful tool to provide specific information for trade-off analysis. Nonetheless, it was criticized that there are some shortcomings, such as less focused on biodiversity, mostly dominated at regional scale, and rarely considered detailed bottom-up economic modeling of land-use management (Kirchner et al., 2015).

3.2 Integrated modeling for trade-off analysis

In comparison with the widely applied GIS-based tool for spatial ecosystem services trade-off mapping analysis, integrated modeling approach can deal with some shortcomings raised above, which not only allows for a spatially explicit quantification of the ecosystem services changes over time and space (Huber et al., 2013), but also can link disciplinary data and models to clarify complex interactions between the human society and the ecosystems (Falloon and Betts, 2010; Laniak et al., 2013). Recently, the integrated modeling approach has been widely applied in the assessment of trade-offs in ecosystem services (Nelson et al., 2009; Polasky et al., 2011; Willemen et al., 2012). For example, Briner et al. (2012) designed an integrative modeling framework-Alpine Land Use Allocation Model (ALUAM), which not only specifically considers the spatial scale at which decisions are made, but also the economic interdependencies among ecosystem services. Further, they applied the ALUAM to evaluate spatially explicit trade-offs among food provision, protection against natural hazards, carbon sequestration, and biodiversity in a mountain region in the Swiss Alps within designed scenarios (Briner et al., 2013).

Among the integrated modeling tools, the most currently available and applied tool is the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) (Nelson et al., 2009; Tallis et al., 2011), which was designed to inform decisions about resources management and planning. Nelson et al. (2009) applied InVEST to investigate the trade-offs between biodiversity conservation and ecosystem services under stakeholder-defined scenarios of land-use/land-cover change in the Willamette Basin. It showed that such trade-offs varied in different scenarios, suggesting that analyzing trade-offs between ecosystem services did great favor in more effective, efficient, and defensible decision makings (Nelson et al., 2009). Goldstein et al. (2012) revealed the trade-offs between carbon storage and water quality and also between environmental improvement and financial returns under seven land-use planning scenarios based on InVEST, which support the implement of the plan for diversified agriculture and forestry management. However, Jackson et al. (2013) pointed out that InVEST was widely applied at large scale and with coarse resolution, in comparison they designed the Polyscape tool, which can be used to disentangle spatially explicit ecosystem services trade-offs to support landscape management, from individual field scale through to catchments scale. Further, they compared the similarities and dissimilarities among different tools, such as Artificial Intelligence for Ecosystem Services (ARIES) tool, Envision Visualization System (EnVision) tool, and the framework and models developed within Multiscale Integrated Earth Systems project (MIMES).

There has been great advances in the development and application of integrated modeling approach for ecosystem services and trade-off analysis, while comparing the dissimilarities among the integrated modeling tools, it can be noted that, considering the spatial differences and regional heterogeneities, there still exist space and opportunities for innovations on multi-scale and multi-regional integrated modeling frameworks for ecosystem services trade-off analysis at a higher spatial resolution (Crossman et al., 2013).

3.3 Multi-criteria analysis of trade-offs

Ecosystem management will inevitably involve conflicting objectives, trade-offs, uncertainties and conflicting value judgments (Sanon et al., 2012), making it a complex process for policy design for ecosystem management. To address above interdisciplinary and complex problems, multi-criteria analysis, as a tool that can take both ecological and socioeconomic criteria into consideration, is mostly applied to conduct ecological economic analysis (Huang et al., 2011; Fontana et al., 2013). Multi-criteria analysis had been applied in various disciplinary researches and recently been broadly introduced and utilized to solve the problems in ecosystem services management (Daily et al., 2009; Nelson et al., 2009). For example, Cheung and Sumaila (2008) applied the multi-criteria analysis to explore the trade-offs between conflicting conservation and socioeconomic objectives for tropical marine ecosystems management.

Traditional multi-criteria analysis deals with only the implicit trade-offs through introducing the weights expressed by the stakeholders (van Huylenbroeck, 1997), to enhance the transparency, Sanon et al. (2012) assigned numerical values for ecosystem services to elaborate and quantify the trade-offs between the stakeholder's objectives based on a participatory approach. In addition, combining the Geographical Information System (GIS) with multi-criteria analysis, Nguyen et al. (2015) proposed a spatial multi-criteria analysis, which integrates ecological aptitude, environmental impact and socio-economic feasibility criteria in a step-wise procedure to analyze objectives that affected by spatially-distributed diagnostic factors. Further, Vollmer et al. (2015) demonstrated an application of a four-step spatial multi-criteria analytical approach that involves scenario development, ecosystem service quantification and mapping, preference weighting, and optimization to maximize preferred ecosystem services while minimizing cost, which can support decision making for efficient polices to manage ecosystem services.

3.4 Trade-off analysis based on production theory

Multi-criteria analysis has a long history of being applied to analyze the trade-offs in ecosystem services, in parallel, the production theory developed by the economics discipline has also been applied to production of ecosystem services (Barbier, 2007) and to examine trade-offs of ecosystem services (Naidoo and Ricketts, 2006). Production theory is a subfield of microeconomics that concerns trade-offs between different inputs for production, i.e. considering the process of different inputs being converted into different outputs (Varian and Repcheck, 2010). A production theory analysis can be linked not only to the ecosystem services with market value as inputs in the production function, but also to the others not connected to market output (Chee, 2004; Barbier, 2007). As that not all services can be simultaneously maximally delivered to humans, thus stakeholders must make decisions according to their preferences, then when applying production theory to ecosystem services trade-off analysis for decision making, the key principle is to achieve the sustainable and efficient delivery of multiple interacting services to human society (Tallis et al., 2008).

The Cobb-Douglas Production functions are the most widely used types to depicts the production theory (Chisasa and Makina, 2013), while it cannot cope with the complex systems that with multiple inputs/multiple outputs production systems that influenced by natural resources, external environmental attributes, and the preferences of land managers. To address the multiple-inputs/multiple outputs production functions, the efficiency frontier method has become popular (Grosskopf et al., 1992), which can be traced back to the ideas put forward by Farrell (1957). Specifically, the productive efficiency is treated as a relative concept, which can be illustrated as Pareto-efficient options for optimal utilization of two or more services, where the system cannot increase one service without sacrificing other services (Nelson et al., 2008; Polasky et al., 2008).

In recent years, the efficiency frontier analysis has been utilized in a variety of researches to examine trade-offs between different ecosystem services, especially in agro-ecosystems (Bekele et al., 2013; Balbi et al., 2015; Mastrangelo and Laterra, 2015). Lester et al. (2013) conducted a review on the ecosystem services trade-off analysis framework that based on economic theory, and summarized six common types of ecosystem service interactions based on the insights gained from frontier shapes, including non-interacting services, direct trade-off, convex trade-off, concave trade-off, non-monotonic concave trade-off, and backward S trade-off. All the frontier shapes focus on two dimensions, which are the easiest ways to visualize, while the concept and logit can be applied to trade-offs in multiple dimensions as well (Cavender-Bares et al., 2015). For example, to deal with the conflicts between the production of marketable ecosystem goods and the provision of non-marketed ecosystem services in agro-ecosystems, Bekele et al. (2013) combined the Soil and Water Assessment Tool (SWAT) model and the productive frontier analysis to analyze a 6-dimensional trade-offs between three provisioning services and three regulating services, which confirmed that provisioning and regulatory services aggregately formed a linear to convex ecological-economic production possibilities frontiers. The efficiency frontier is an effective method to judge the biophysical constraints of the ecosystem services production system, which combines with the information about value of services from stakeholders' perspective, and further identifies optimal management approaches that yield the greatest net benefits, while the problem that there may exist uncertainty about the production frontier and values still remains to be dealt with (Cavender-Bares et al., 2015).

4 Conclusions

For ensuring sustainable land-use management, it is critical to conduct trade-off analysis of ecosystem services closely associated with land-uses, which allows the decision-makers to better understand the corresponding consequences of different choices and achieve a solution to long-run sustainable development of socio-ecological systems.

Trade-offs arise when biophysical constrains change or humans make management interventions, which will change the types, magnitudes and interactions among services provided by ecosystems. Investigations on the trade-offs among individual ecosystem services and biodiversity are mostly provoked, further analysis on the interactions among ecosystem services bundles has also gained great achievements. On one hand, intensive land-use change and management are recognized as the major factors affecting ecosystem services provisions and incurring trade-offs, on the other hand, the major barriers that inhabit the sustainable resource planning and management contribute to ecosystem services trade-offs at different scales, which can be classified in terms of temporal and spatial scale, stakeholders' preference, and the degree of irreversibility. Thus, taking the ecosystem services trade-offs at different scales into consideration during decision-making is important for sustainable land use management to avoid negative effects and achieve synergetic outcomes.

In dealing with the problem of ecosystem services trade-offs, a wide variety of analytical tools and approaches have been developed and applied for management decisions, including the assessments that explicitly linked spatial information on service supply to conduct correlation or cluster analysis, the integrated modeling framework for the systemic assessment, and also approaches based on the multi-criteria decision theory and economic production theory. While, evaluation of trade-offs is complex due to the multiple dimensions, interactions, variations and uncertainties with different physical units across time and space, thus quantifying the non-linear dynamics of trade-offs between ecosystem services in the social-ecological systems driven by both biophysical drivers and management decisions still remains a big challenge for sustainable land-use management.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgements

This research was supported by China National Natural Science Funds for Distinguished Young Scholar (Grant no. 71225005) and the Key Project in the National Science & Technology Pillar Program of China (Grant no. 2013BACO3B00).

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Chapter 3: Relationship Between Landscape Diversity and Crop Production: A Case Study in the Hebei Province

This paper has been published in the *Journal of Cleaner Production* 142, 985–992.

Abstract

This paper explores the relationship between landscape diversity and crop production using big data techniques. In the case study area of Hebei province, China, there is a positive ecological effect of landscape diversity on crop production (coefficient of H (Shannon's index) and H^2 on crop production are 7.9665 and -2.2388, respectively), and a negative effect via operating cultivated land change (coefficient of H and H^2 on cultivated land change are -5.4253 and 1.5520, respectively). This negative effect is measured with big data techniques and is explained by variables such as the ratio of cultivated land and other basic local conditions. The net effect of landscape diversity on crop production is negative, all else the same, reflecting the strength of the impact through cultivated land change. Thus, it is important to adhere to a certain level of landscape diversity if crop production is to be sustained.

Keywords: landscape diversity, crop production, big data, data fusion, Shannon's index

1 Introduction

Urbanization and economic growth cause remarkable changes of landscape patterns which are identified by the mosaics of cropland, woodland, built-up land, forests, meadows, and so forth (Palacios et al., 2013). Landscape change and cultivated land conversion due to urbanization and industrial transformation can lead to severe habitat destruction as chequered landscapes are formed (Fu and Chen, 1996; Schindler et al., 2013). Dynamics of landscape patterns may alter a variety of natural flows and wildlife abundance (Romme and Knight, 1982), and also may affect crop production (Boreux et al., 2013). The phenomena seem to be more obvious in major agricultural production regions.

The Hebei province of China, located on the periphery of Beijing and Tianjin and north of the lower reaches of the Yellow River with Bohai Sea to the east (113°27'-119° 50'E, 36°05'-42°40'N), is a salient case study of these processes (Fig. 1). Hebei province, with an area of 190,000 km^2 and a population of 71.85 million in 2010 (10.16 million of them live in the capital city, Shijiazhuang), is one of China's major bases of agricultural production. It has a continental monsoon climate, with cold, dry winters, and hot, humid summers. The temperature is −16 to −3 °C in January and 20 to 27 °C in July, with annual precipitation ranging from 400 to 800 millimetres, concentrated heavily in summer. Favourable climate and land resources contribute to the historical and current agriculture development, with over 80% of cropland in wheat, corn, broomcorn, millet, etc. Recent rapid urbanization witnesses the growth of the population living in urban areas in Hebei province, which increased by 10.5 percent from 2006 to 2014. Even though it has the same increasing percentage with the entire China, Hebei province has a faster rate since it started with a lower proportion of urban dwellers (38.8% compared with 44.3% for China, calculated by urban population divided by total population of Hebei province) (NBSC, 2007- 2015). The resulting land conversion changed landscape patterns and threatened crop production at both local and regional level.

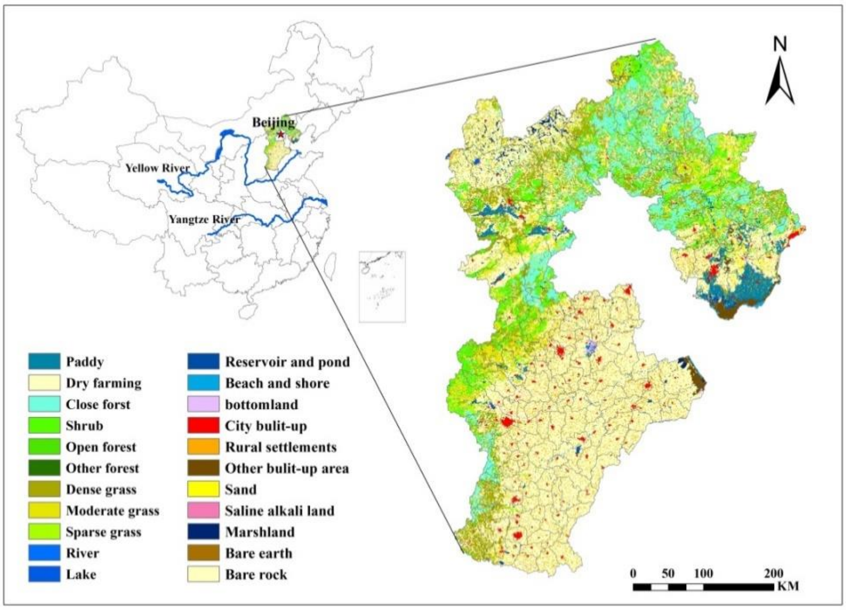


Fig. 1. The location of the study area and the patterns of land use/cover in 2008

While rapid urbanization and land conversion are common throughout eastern China, Hebei province is of special interest as an experimental site for industrial transformation, new urbanization and environmentally friendly development (the Plan for Cooperative Development of Beijing-Tianjin-Hebei (Jing-Jin-Ji)). The evolution of the industrial structure is shown by the declining importance of the primary and secondary sectors and the rise of the tertiary (services) sector; in 2010 the contribution percentage of the three sectors were 12.6%, 52.5% and 34.9%, separately, while in 2014 they were 11.7%, 51.1%, and 37.2%, separately (NBSC, 2011, 2015). Considering the fundamental character of the primary sector, crop production is emphasized due to the limited cultivated land resources. Meanwhile, the Grain for Green Program implemented in Hebei province has resulted in 6313 km^2 (over three percent of total land area) of cultivated land transformed to forestry land since the program launch in 2002. This ecological restoration project also affects the dynamics of landscape in Hebei province.

1.1 Overview of the impact of landscape diversity on crop production

The impact of landscape diversity on crop production is ambiguous (Le Féon et al., 2010; Benoît et al., 2012; Sayer et al., 2013). On the one hand, loss of landscape diversity affects the environment due to the loss of biodiversity and the declining function of other ecosystem services (Kareiva and Wennergren, 1995; Guerry and Hunter, 2002; Midgley, 2012). The Millennium Ecosystem Assessment (MA) noted that ecosystem changes affecting food production, freshwater, timber, fuel supply that are induced by land use and land cover change (LUCC) may harm human well-being (MEA, 2005), while the Global Land Project (GLP) declared that there is a close relationship between land use change, ecosystem evolution and human production activities (GLP, 2005). The Pan-European biological and landscape diversity strategy (PEBLDS) and FAO's paradigm for enhancing productivity and sustainability all call for ecosystem approach drawing on natural contribution to agriculture (Council of Europe, 1996; FAO, 2011; Naeem et al., 2012). Peterjohn and Correll (1984) notes that landscape diversity that helps retain or transform nutrients through underground water is an essential driver of crop production. Furthermore, as nutrient flows are altered by landscape change, the crop production is affected in tandem. Petersen and Nault (2014) highlight the role of bees as mediators between landscape features and crop production. A fair summary of these studies is that the evolving landscape diversity associated with land use change influences on crop production via ecosystem services (Solan et al., 2008; Mace et al., 2012).

On the other hand, a loss of landscape diversity may occur with expansion of a certain type of land. Moreover, it is difficult to capture all aspects of diversity in a single statistic (Gorelick, 2013; Rocchini et al., 2013). For example, in Fig. 2, the landscape A is comprised of cultivated land and land use/cover type *i*, and these two types of land cover each account for 50%, separately. In contrast, landscape B has five land use/land cover types, with cultivated land accounting for 90%, and the other four combining accounting for 10%. According to the landscape metrics, commonly used to measure the landscape diversity in terms of richness and evenness (Nagendra, 2002), the landscape A is more diverse than B. Yet, landscape B may be capable of producing more grain because of the large amount of the cultivated land and the expanding tendency. Thus, it is important to empirically estimate the relationship between the landscape diversity and crop production for an effective landscape management.

Asides from the possible ambiguity between landscape diversity and crop production shown in Fig. 2, researchers also need to recognize that the relationship may change over time and may be context-specific with regional character. The effects of landscape diversity on crop production may occur through two pathways: an ecological effect and an economic effect. The ecological effect can be considered as a direct effect on the land quality while the economic effect preforms indirectly by influencing crop production through changing the amount of cultivated land. The net effects of landscape diversity on crop production depend on whether the economic effect outweighs the ecological effect.

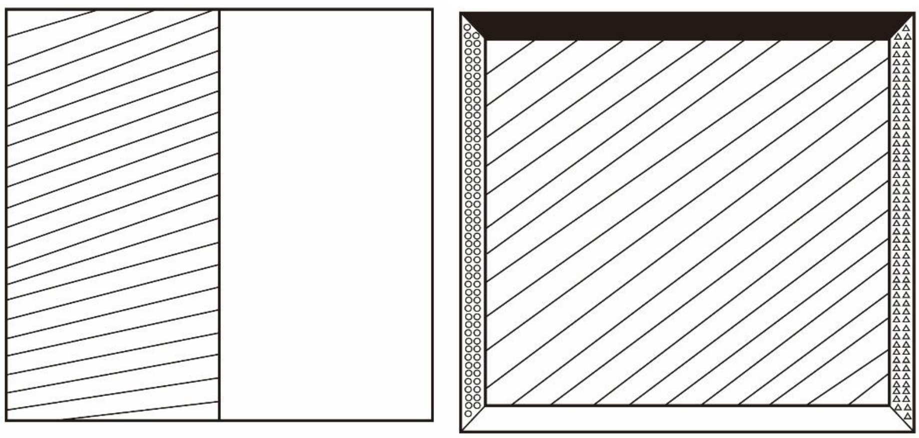


Fig. 2. The assumed landscape patterns for comparing landscape diversity and potential crop production.

1.2 Big data techniques

We study the relationship between landscape diversity and crop production in Hebei province using big data techniques. These refer to integrated techniques for handling and applying multi-source and multi-scale data for scientific research (Waltz and Llinas, 1990; Hall and McMullen, 2004). The idea of data fusion and linked technical protocols originated in the 1970s, and has developed remarkably in recent years. For example, integration of spatial data with socio-economic data achieved the geographic positioning of multi-source information, which is known as “socializing the pixels”, the technology can be dated back to the 1990s (Geoghegan et al., 1998; Deng et al., 2008). A specific case related to management of resources and the environment is the development of 1-km area percentage data, combining the advantages of grid data with vector data, by fusing global or regional multi-source data (Liu et al., 2003; Deng et al., 2010). We follow these developments in this paper, by combining multiple data sources from geophysical and socio-economic domains, to explore how landscape diversity affects crop production in Hebei province.

Due to the uncertainty of the net effects of landscape diversity on crop production, we first explore relationships between landscape diversity, the cultivated land ratio and crop production using scatter plots. Next, the relationship between landscape diversity and cultivated land change is further examined by econometric analysis. Then quantitative analysis is carried out to identify tradeoffs from how landscape diversity influences crop production. Finally, the lessons from the relationship between landscape diversity and crop production in Hebei province are summarized and the paths for future research are discussed.

2 Methods

2.1 Data

Previous research on determinants of crop production is abundant due to pressing issues on food waste, food security, the increasing demand for food, and for sustainable agriculture (FAO, 2015). A prior contribution by Xie (1999) notes that crop production is affected by ten major factors--labor, sown area, irrigated area, mechanic tillage area, fertilizer use, pesticide use, rural electricity consumption, total power of agricultural machinery, total power for irrigation, and drainage and plastic mulch. More variables, in term of biophysical and socio-economic domains, were included in a study of China's counties (Huang et al., 2010). Here, we take the following factors into consideration: the number of agricultural labors, the ratio of cultivated land, fertilizer usage, electricity for rural use, the agricultural machinery, and landscape diversity. The statistics summary of these variables and the related total crop production (y) are shown in Table 1 for all counties in Hebei province with non-missing values of these variables in each of the studied five years.

Table 1: The description of variables used in this study.

Variables	Unit	Obs.	Min	Max
Crop production (*y*)	*Tonne*	745	12275	679916
Agricultural labors (*agrlbr*)	*Person*	745	17504	393973
Electricity for rural use (ElecRurUse)	*10,000 kWh*	745	310	285390
Fertilizer use (*fertUse*)	*Tonne*	745	442	74109
Agricultural machinery (*agrMach*)	*Kilowatt*	745	7.8	2171100
Ratio of cultivated land (*R*)		745	0.0567	0.7340
Landscape diversity (*H*)		745	0.8645	2.2803

The first data sources, the cultivated land ratio and landscape diversity are calculated from 1-km area percentage data in the year of 1988, 1995, 2000, 2005 and 2008, which were derived from Landsat Thematic Mapper (TM) or Enhanced Thematic Mapper(ETM) and China–Brazil Earth Resources Satellite (CBERS) digital imagines, with an interpreted accuracy of 94.3% (Liu et al., 2013). The second source, for the crop production, agricultural labors, fertilizer use, agricultural machinery and electricity for rural use, came from provincial and county statistic yearbooks for Hebei province in the same time period. We selected 149 of out of the entire 172 counties of Hebei province and collected the above-mentioned dataset.

2.2 Indicators

2.2.1 Ratio of cultivated land

In this study, cultivated land refers to both paddy field and dry land, which obey the land use classification system of remote sensing data provided by the USGS Landsat TM/ETM with an original spatial resolution of 30 m. And the ratio of cultivated land here is incorporated as an essential control variable in the econometric analysis on landscape diversity and crop production. These were aggregated to the total amount for each county (S_c), expressed as a percentage of the county's total land area (S_{land}):

$$R = \frac{S_c}{S_{land}}$$

2.2.2 Landscape diversity

Landscape diversity metrics are designed to capture *richness* and *evenness*, where richness refers to the number of different landscape types in an area; more diverse areas have more landscape types. Landscape evenness reflects the percentage (of total area) distribution amongst different landscape types and it would be higher when there is a more balanced distribution. We used Shannon-Wiener index (H) to measure these aspects of landscape diversity in Hebei province, noting that other aspects of a landscape such as size, perimeter and shape also may be used (Zhou et al., 2014; Duflot et al., 2015). Shannon's index was developed to show variance in species abundance distributions, and we adopt it to show variance in the proportion of area covered by each of 25 land use types (Gardiner et al., 2009). The Shannon diversity index (H) is expressed as:

$$H = -\sum_{i}^{m} P_i \, lnP_i$$

where P_i is the proportion of an area in land-use type i, and m is the total number of land-use types. The Shannon diversity index indicates the heterogeneity of landscape, and as the value of H rises, a landscape is getting more diverse and the degree of evenness will also be increasing (Nagendra, 2002). At the extreme situation, when m equals to 1, there is only one type of landscape in an area and H would be valued as zero.

2.3 Modeling

2.3.1 Potential trade-offs of landscape diversity versus cultivated land change

We use panel data with up to five observations on each county to model three relationships: the relationship between landscape diversity and the cultivated land ratio; the relationship between the cultivated land ratio and crop production; and finally, the relationship between landscape diversity and crop production while controlling for other factors (including the cultivated land ratio). The first relationship can be written in general as:

$$R_{it} = g(H) + v_{it} \tag{1}$$

where R_{it} is the ratio of cultivated land in county i and year t, H is landscape diversity for that county and year and v_{it} is a random error term.

The empirical relationship between landscape diversity and the cultivated land ratio should reflect the following conditions:

(i) There is always some cultivated land in a county, so that is, R>0,

(ii) As landscape diversity increases from a more even distribution, then the cultivated land area approaches zero (Fu et al., 1996): $\mathrm{H} \to \infty \Rightarrow R \to 0$,

(iii) As cultivated land rises and approaches the total land area, landscape diversity approaches zero, that is: $\mathrm{R} \to 1 \Rightarrow H \to 0$.

The conditions match features of exponential or logarithmic functions, so equation (1) could be estimated in either of two forms:

$$R_{it} = \alpha_0 + \alpha_1 H_{it} + \alpha_2 H_{it}^2 \tag{2}$$

or

$$\ln(\mathrm{R}_{it}) = \beta_0 + \beta_1 \mathrm{H}_{it} \tag{3}$$

A comparison of R^2 values after the predictions from equation (3) were transformed to levels to be comparable to the predictions from equation (2) suggested the quadratic form was slightly more consistent with the data (R^2=0.546 compared with 0.478 for the transformed equation (3)), so equation (2) is used.

In terms of the second relationship, between crop production and the cultivated land ratio, Liu et al. (2013) and Xu et al. (2014) have proved that cultivated area is related with crop production, this can be expressed as:

$$\ln(y_{it}) = \theta_0 + \theta_1 R_{it} + \theta_2 Z_{it} \quad (4)$$

where Z_{it} refers to the other control variables. The recursive effect of landscape diversity on cultivated land (via equation (2)) and then of cultivated land on crop production provides an indirect pathway of influence from changes in landscape diversity.

2.3.2 Multivariate relationship between landscape diversity and crop production

In addition to the direct effect of landscape diversity on crop production, and the indirect effect via the cultivated land ratio, we also control for human, chemical, and power inputs into crop production. These inputs are: *agrlbr* which is agricultural sector employees, *fertUse* is total fertilizer use, *agrMach* is total power of agricultural machinery, and *ElecRurUse* is electricity consumption for rural areas which are all reported at county level by China's statistics agency:

$$y_{it} = f(agrlbr_{it}, agrMach_{it}, ElecRurUse_{it}, fertUse_{it}, R_{it}, H_{it}, H_{it}^2) \quad (5)$$

From equation (5), $\frac{\partial f}{\partial H_{it}}$ is the direct effect of landscape diversity on crop production, and the indirect effect operating through R_{it}, denoted as $\frac{\partial f}{\partial R_{it}}\frac{\partial R_{it}}{\partial H_{it}}$. Using logarithms for all variables except R_{it} (which lies between zero and one) and also for landscape diversity whether the quadratic relationship was established above, we have:

$$\ln y_{it} = \gamma_0 + \gamma_1 \ln agrlbr_{it} + \gamma_2 \ln agrMach_{it} + \gamma_3 \ln fertUse_{it} + \gamma_4 \ln ElecRurUse_{it} + \gamma_5 R_{it} + \gamma_6 H_{it} + \gamma_7 H_{it}^2 + u_{it} \quad (6)$$

where variables are noted above and u_{it} presents the random error term.

3 Results

3.1 Relationship between landscape diversity and cultivated land ratio

As shown in Fig. 3, the tendency of cultivated land ratio is to decrease with the increase of landscape diversity. As described above, the research on landscape diversity concludes landscape patch diversity, landscape type diversity and landscape pattern diversity (Jha and Kremen, 2013). While landscape diversity attaches to ecosystem via its *richness* and *evenness*, the size of each landscape has an influence on the distribution of energy and nutrients affecting the species' growth (Hansen and DiCastri, 2012; Paudel and Yuan, 2012). Therefore, landscape diversity interprets both of the ecological significance and land use pattern in a certain region. And the impact of landscape diversity upon crop production could be sensed and represented as ecological effect which is shown directly and the indirect effects of economic production associated closely with cultivated land changes. These two connotations should be separated if we determine to figure out its ecological impact.

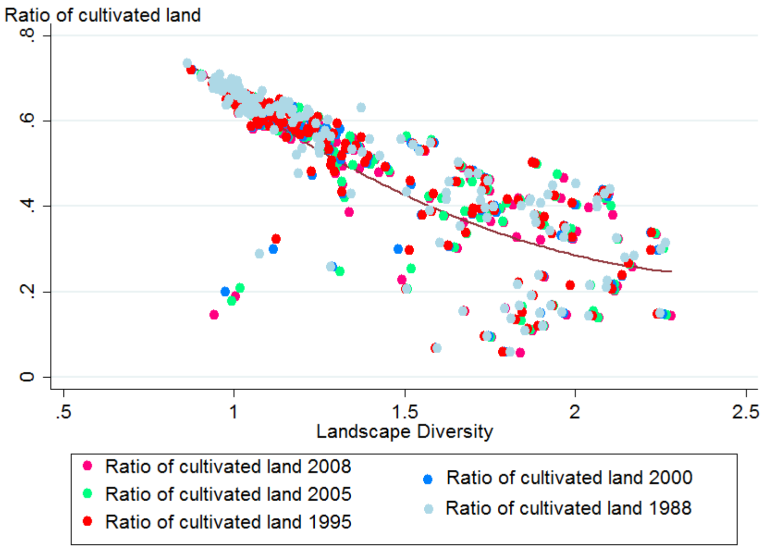


Fig. 3. The relationship between the ratio of cultivated land (*R*) and the landscape diversity (Shannon's index, *H*) of Hebei province in 1988, 1995, 2000, 2005, and 2008. Both of them were calculated by land use data interpreted from remote sensing (see *Methods: Indicators*). Each color of the spots corresponded to the samples of each year.

Quantitative analysis illustrates that the tendency of the ratio of cultivated land is to decrease with the increase of landscape diversity. Considering the attributes of the data set, panel data model is adopted to quantify the relationship between landscape diversity and cultivated land ratio. The panel data model could be classified into two types in the light of the heterogeneity of the sample, namely the fixed effects model and random effects model. Therefore, we choose the model in the light of the results of the Hausman test. Most econometrics analysis made the choice between random effects model and fixed effects model were based upon the standard Hausman test (Baltagi, 2008; Hahn et al., 2011). If the standard Hausman test rejects the null hypothesis that the conditional mean of the disturbances given the regressor is zero, the applied researcher adopts the FE estimator. Otherwise, it is quite often to adopt the RE estimator (Baltagi et al., 2003). The estimation result of Hausman test indicates that fixed effects model seems to be more appropriate for clarifying their interaction

(P>chi2=0.00).

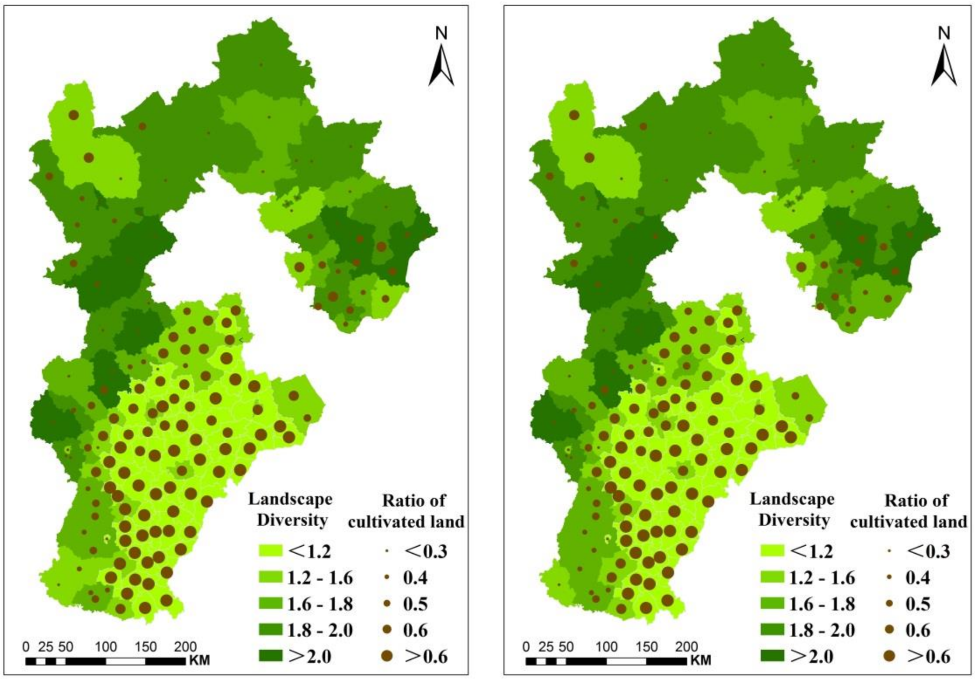
Then, according to equation (2), the equation (8) is generated:

$$\mathrm{R}_{it} = 9.1420 - 5.4253H_{it} + 1.5520H_{it}^2 \tag{8}$$

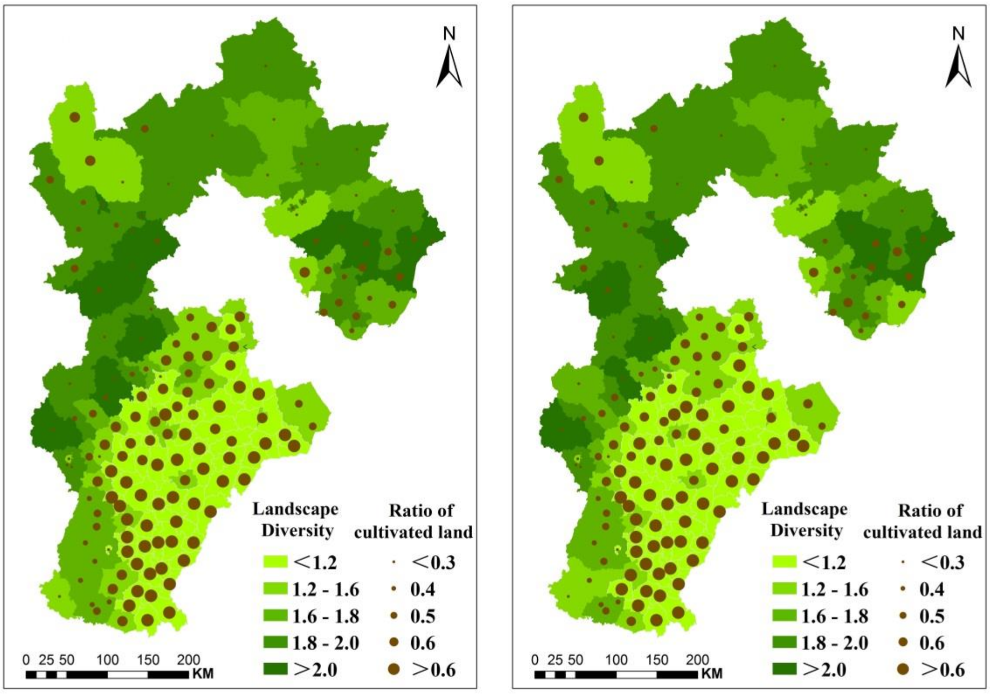
Equation (9) is generated in the light of equation (3).

$$\ln\mathrm{R}_{it} = 1.5336 - 0.05076H_{it} \tag{9}$$

Compared with equation (9), the equation (8) specification better fitted the distribution of samples, which shows that there exists a non-linear relationship between the ratio of cultivated land and landscape diversity, which generally indicates that cultivated land will decrease with increase in landscape diversity. In addition, we mapped the spatial variation in landscape diversity onto that of ratio of cultivated land, using GIS technology (Fig. 4). The spatially explicit pattern of landscape diversity and ratio of cultivated land with county administrative zoning also demonstrates their relationships.



Panel A Panel B



Panel C Panel D

Fig. 4. Distribution of landscape diversity (*H*) and ratio of cultivated land (*R*) in county level of Hebei province in 1995 (panel A), 2000 (panel B), 2005 (panel C), 2008 (panel D). The landscape presents more diverse with the color goes deeper, the ratio of cultivated land is higher as the spot goes larger. The lightly colored region possessed spots which were larger than those of the deep colored region.

3.2 Specification of the relationship between cultivated land and crop production

As shown in Fig. 5, both growth of ratio of cultivated land and crop production are increasing. This relationship is in accord with the previous studies (Matson et al., 1997; Boserup et al., 2005; Deng et al., 2006; Ray et al., 2013). Their researches maintain a consistent perspective that cultivated land is one of essential elements for crop production and links with food security (Fader et al., 2013).

In summary, both model (8) and model (9) indicate there is a nonlinear relationship between landscape diversity and cultivated land change. Fig. 5 also shows that crop production is positively related with ratio of cultivated land. All these support our perception that landscape diversity apparently affects crop production in our case study area of Hebei province.

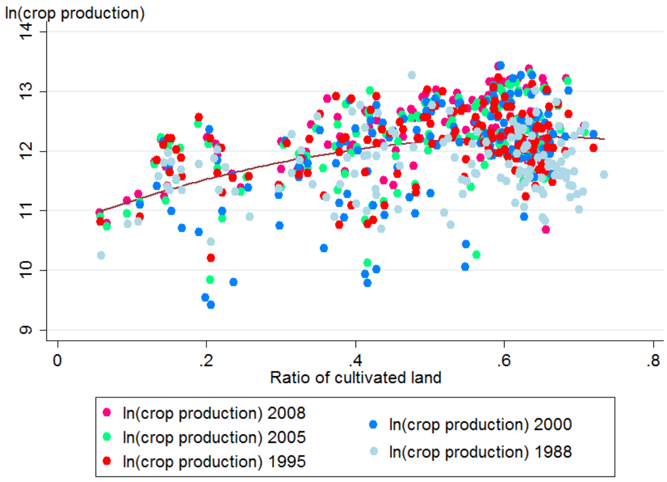


Fig. 5. Relationship between ratio of cultivated land (*R*) and crop production (in logs) of Hebei province in 1988, 1995, 2000, 2005, 2008.

3.3 Quantitatively measured effects of landscape diversity on crop production

Fig. 6 presents the overall effects of landscape diversity on crop production, of which actually originates from two path as the analysis indicates, one is its ecological impact as the loss of landscape diversity which remind us the issue of biodiversity loss and ecosystem degradation. The other is that landscape change which is represented as the variation of Shannon's index is closely related with area change of cultivated land area, which actually considered as one of the critical factors affecting crop production.

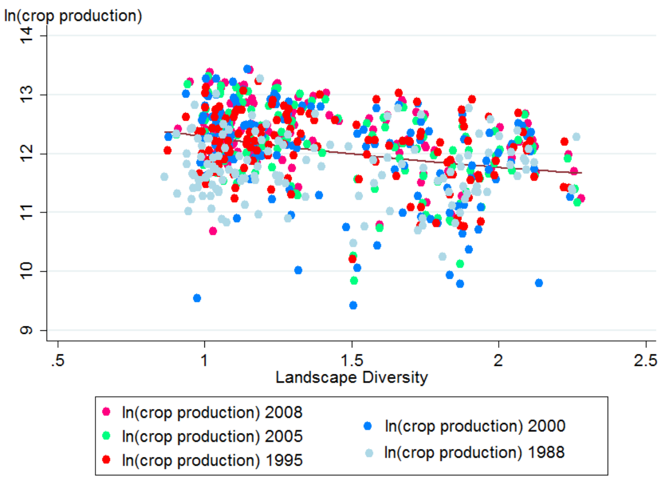


Fig. 6. The overall effects of landscape diversity (*H*) on crop production of Hebei province in 1988, 1995, 2000, 2005, 2008.

In order to catch both of these effects, equation (6) is estimated at first. Here is the result shown in Table 2.

Table 2: Regression results of fixed effects model based on equation (6) for identifying the relationship between landscape diversity and crop production by controlling variables.

	Equation (1')	Equation (2')	Equation (3')	Equation (4')	Equation (5')
H	3.0912	12.5816	10.6051	10.8573	7.9665
	(5.20)***	(5.93)***	(4.97)***	(5.11)***	(5.31)***
H^2		-3.5854	-3.0200	-3.0269	-2.2388
		(-4.57)***	(-3.86)***	(-3.89)***	(-3.90)***
R			-0.3643	-0.3451	0.0248
			(-4.45)***	(-4.22)***	(0.26)
ln(agrlbr)				0.1635	0.0757
				(2.73)***	(1.13)
ln(fertUse)					0.2718
					(5.08)***
ln(EleRurUse)					0.0549
					(2.36)**
ln(agrMach)					0.0082
					(1.87)*
Constant	7.6420	1.9386	5.2692	2.9487	1.4442
	(8.96)***	(1.39)	(3.37)***	(1.67)*	(0.81)
Hausman test	Chi2(8)=(b-B)'[(V_b-V_b)^(-1)](b-B)=195.58				
(equation 5')	Prob>chi2=0.0000				

*Note: * p<0.05; ** p<0.01. And the result of equation (6) indicates that agricultural labours and cultivated land ratio is insignificant in fixed effects model, but these two variables cannot remove because of their crucial contribution to crop production. Result of Hausman test indicates fixed effects model is better.*

The model for evaluating the effect of landscape diversity could be written as:

$$\ln y_{it} = 1.4442 + 0.0757 lnagrlbr_{it} + 0.2718 lnfertUse_{it} + 0.0549 lnEleRurUse_{it} + 0.0082 lnagrMach_{it} + 0.0248 R_{it} + 7.9665 H_{it} - 2.2388 H_{it}^2 \qquad (11)$$

As equation (11) indicates, there is a considerable contribution of landscape diversity on crop production as could be regarded as an ecological effect supplied by landscape. It is noticeable that the effects identified by the magnitude of the estimated elasticity is quite small which further indicated the potential contribution of landscape diversity on crop production is marginal via supplying the so-called ecological effects.

4 Conclusions and discussion

4.1 Conclusions

This paper contributes to quantitatively measure and present the effects of landscape diversity on crop production in terms of direct and indirect impact by using the Shannon's index. Based on the multi-source data of 1988, 1995, 2000, 2005 and 2008, we screened agricultural labors, ratio of cultivated land, agricultural machinery, fertilizer use, electricity for rural use, and landscape diversity as the independent variables to explain crop production. Then, the explicit interaction of landscape diversity and crop production is extracted in the light of the results run by the model.

(i)Landscape diversity influence crop production from two separate aspects, namely the ecological impact and the impact of cultivated land change induced by landscape variation, the former one is directly reflected in the index of Shannon's index, and the latter one is accounted with the change of landscape diversity.

(ii) Ecological impact induced by landscape diversity is positively associated with the crop production.

(iii)Landscape diversity does not correlate linearly with cultivated land change (equation (8), Fig. 4, Fig. 5). And cultivated land is performed as one of the essential factors influence the crop production significantly (equation (10)).

(iv)Landscape diversity is positively correlated with crop production as the marginal ecological impact is larger than the marginal impact of cultivated land change. Then, it negatively affects crop production when it is out of the premise.

Lessons of Hebei province imply that maintaining a certain number of landscape diversity benefits the crop production, nevertheless, it is adverse as the landscape diversity exceeds the certain range. But landscape diversity possesses the priority for enriching the biodiversity enhanced the competition between pests and their predators. Pursuing crop production should take the advantages of landscape diversity into account. The agricultural input such as agricultural machinery, fertilizer and electricity could also increase the crop production, strengthening the construction of infrastructure is the feasible and practical way for advancing crop production.

4.2 Discussion

Given that there is quite few of relevant studies focusing on evaluation of significance of landscape pattern to crop production, most of the researches listed in literature review part are focused on the ecological effects of landscape diversity. And we design and conduct an empirical study to explore the relationship between landscape diversity and crop production from two sides, namely ecological effects and economic effects. Calling for the concern of landscape diversity as it highlights ecological preservation, while the increased landscape diversity may reduce the cultivated land area threatening the crop production is seldom mentioned. Moreover, the data fusion of landscape diversity, ratio of cultivated land and regional information of Hebei province has visualized the internal junction of the two indicators by the big data technology. It provides the basic evidence for exploring the further links of landscape diversity and crop production.

Apart from that, this study has not answered the question on how much extent the landscape diversity impact the crop production, where the threshold of the growth of crop production with landscape diversity. We have just adopted Shannon's index to represent landscape diversity, which has been proved defective and cannot express the spatial dynamics of landscape very well. Thus, further research is still needed to meet the research needs.

Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This research was financially supported by the National Natural Science Funds of China (Grant No. 71225005; Grant No. 41171434) and the Key Project in the National Science & Technology Pillar Program of China (no. 2013BAC03B00).

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Chapter 4: Sustainable Land Use Management for Improving Regional Eco-efficiency: A Case Study of Hebei, China

This paper has been published in *Annals of Operations Research*
https://doi.org/10.1007/s10479-018-2874-3.

Abstract

Land cover is being continuously transformed at an accelerating pace because of urbanization and economic development, which is, in turn, impacting ecosystem services and human well-being. Consequently, there is a need to enhance sustainable land use management to achieve high levels of land eco-efficiency across different regions in China. Accomplishing this entails adjustments not only in terms of the spatial layout of land but also in land use management. The relationship between land use management and land eco-efficiency was explored taking Hebei, a province of China, as a case study. With the help of Stochastic Frontier Analysis (SFA) and other statistical analysis, we analyzed land use conversions and land eco-efficiency in Hebei, China. In this study, we first explored the relationship between land use conversion, ratio of cultivated land, and crop production using scatter plots. Further, we analyzed the land eco-efficiency and ecological performance of cities in Hebei based on SFA. The findings of the study revealed that land use output is the key factor linking land use management and land eco-efficiency. Spatial differences of land eco-efficiency are clearly apparent in Hebei, and the results of the study showed a corresponding decrease in land eco-efficiency with a reduction in the distance to the city center. In conclusion, a step-by-step regulatory process for improving land eco-efficiency within China's land use management scheme is proposed.

Keywords: Land use management · Land use conversion · Land eco-efficiency · Stochastic Frontier Analysis · Hebei

1 Introduction

Current processes of urbanization and economic development are inducing marked changes in land use (Palacios et al. 2013). Land use change and the cultivated land conversion caused by urbanization and industrial transformation are leading to severe habitat destruction (Schindler et al. 2013), affecting a variety of natural flows and wildlife abundance and possibly influencing crop production (Romme and Knight 1982; Boreux et al. 2013). These phenomena seem to be especially significant in major agricultural production regions (Zeng et al. 2016). The findings of comprehensive studies on land uses, have led to growing acknowledgment of the urgent need to address the key issue of land use management within studies of global environmental change (Deng et al. 2016; 2017). In recent decades, human activities have greatly transformed the terrestrial surface of the earth through changes in land use management (Foley et al. 2005). Spatially focused studies that examine land use management and elucidate the interactions between human activities and natural processes will provide important lessons that will yield a better understanding of future changes in the earth system, including those related to land uses, the climate, and associated changes in human societies and economies (Lambin and Meyfroidt 2011).

Land use in China have undergone dramatic changes in recent decades, with manifold implications for sustainable development (Jiang et al. 2013). Investigations and projections of land use management have therefore become critical for developing a deep understanding of land use processes and their interactions with ecosystems and human societies. Whereas urbanization results in numerous benefits, its occurrence at a rapid pace also causes the intensification of resource scarcity and environmental degradation in developing countries, including China. According to the latest report released by the Ministry of Land and Resources of the People's Republic of China, the total cultivated land area in China had shrunk to 123.4 million ha in 2003, which accounts for only 41% of the global average. At present, only 12.8% of the total terrestrial surface in China is available for agricultural production. In this context, the concept of land eco-efficiency has assumed prominence. Land eco-efficiency is closely linked to effective and sustainable use of land resources. The concept of ecoefficiency couples the concepts of "ecology" and "economy". There is no absolute standard for measuring land eco-efficiency, but land eco-efficiency will change with socioeconomic activities that related to land-based production. With the prerequisites of not affecting land or economic outputs, the land eco-efficiency can be improved through the reduction of land resource inputs.

Land use conditions can have various effects on eco-efficiency in different regions, especially on land eco-efficiency of agricultural production. This is because the inputs and outputs of agricultural production are closely associated with eco-efficiency (Deng et al. 2016; Bai et al. 2017). Although ecologists and conservation biologists focus primarily on biodiversity conservation in non-agricultural lands, a strictly conservation focus is acknowledged to be limited in scope, particularly in terms of fulfilling production requirements (Godfray et al. 2010; Chappell and LaValle 2011).

To achieve greater economic benefits, large stretches of unused land have been converted into areas subjected to intensive forms of commercial use, leading to increasing homogenization of natural land uses (Sunderland 2011). Scientists are now increasingly attending to impacts of land uses on the biodiversity of agricultural crops and fauna within farmland as well as on the biodiversity of entire regional land uses for food production (Sonter et al. 2015). Typically, farmers' incomes from food production that are influenced by land use conversion have been analyzed at three levels: ecosystems, species, and genetic diversity (Verburg et al. 2011). The development of techniques for assessing the value of ecosystems may enable the impacts of land use change on food production to be evaluated (Verburg et al., 2013). The conventional model applied to achieve this goal is a comparative analysis of trends in land use change and food production (Díaz et al., 2015).

In Hebei Province of China, the issue of cultivated land conversion, which is expected to impact on crop yields and ecosystem services, has been brought to prominence by urban expansion. In particular, many genetic resources are contained within farming systems and within the broader landscape (Song et al., 2014; Díaz et al., 2015). At the same time, agricultural incomes constitute a large component of farmers' incomes. Consequently, in Hebei, land use conversion caused by rapid urbanization is threatening food production, which directly influences farmers' incomes. However, questions of the extent to which farmers' incomes are influenced and the effectiveness of policies that have been implemented to improve the status of farmers remain to be answered. Thus, it would be advantageous to develop a better understanding of the process of managing land use conversion. This study addresses these questions, and offers solutions and suggestions derived from the application of economic models.

In this study, we used Stochastic Frontier Analysis (SFA) to calculate land eco-efficiency, which is a useful analysis tool to measure efficiency. SFA analysis allows random shocks and measurement error, and it is also possible to analyse the structure and the determinants of producer performance. Based on the above advantages, we selected this method to conduct the efficiency measurement, which is one of the most significant advancements of this study. Because of the prevailing uncertainty about the net effects of land use conversion on crop production, we first explored the relationship between land use conversion, the ratio of cultivated land, and crop production using scatter plots. Further, the land eco-efficiency and ecological performance of cities in Hebei were quantitatively assessed. Last, implications from the analysis on conversion of land use and crop production in Hebei for future research are discussed.

2 Study Area

Hebei is one of China's main agricultural production bases, evidencing high levels of population and economic growth and traditional agricultural production. However, a lack of congruence between land use management and cropping returns for farmers in the province is becoming increasingly apparent. Hebei is located in the North China Plain (113°27'–119°50'E 36°05'–42°40'N) and covers an area of 190,000 km^2(Fig.1).

The climate in Hebei is characterized as temperate continental. January is the coldest month, with temperatures ranging between -22 and -3 ºC. The annual average precipitation ranges between 400 mm and 800 mm.

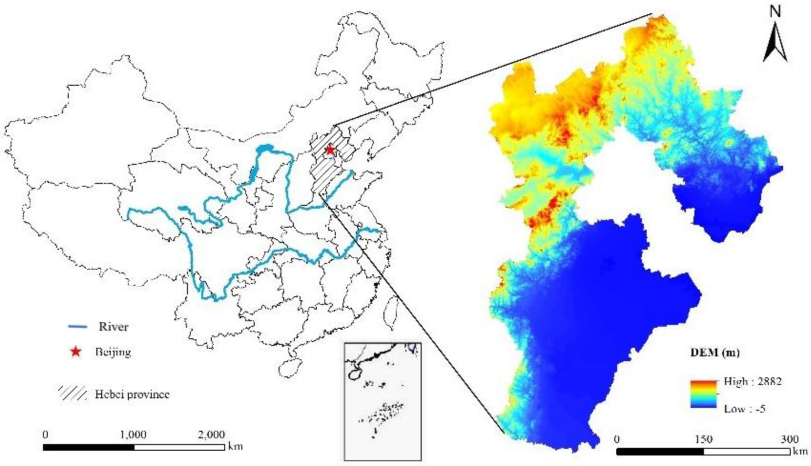

Fig. 1 Geographical location of Hebei Province

Rapid urbanization and industrial development have led to extensive land use conversion in Hebei. During the period 1988–2015, the built-up area of the province increased by more than 10% (3536 km^2), while the area of cultivated land decreased by 4% (2655 km^2). The conversion of cultivated land and the expansion of built-up land clearly indicate that urbanization is propelling the demand for built-up land at the expense of other types of land uses. The *Grain for Green Program* implemented in Hebei has resulted in the transformation of 6313 km^2 of cultivated land into forest land since 200 2(Xu et al., 2006; Deng et al., 2014). During the period 2010–2015, the percentages of the three industrial sectors changed from 12.6, 52.5, and 34.9% to 11.7, 51.1, and 37.2% for the primary, secondary, and tertiary sectors, respectively (NSBC 2011-2016). The decreasing percentages of the output values of the primary and secondary industrial sectors demonstrate the pattern of evolution of the industrial structure. Considering that the primary industrial sector is the core sector, and that cultivated land resources are limited, crop production is emphasized by the government. Both the urbanization process and the ecological restoration project are affecting land use management and threatening crop production at local and regional levels.

3 Data and Methodology

3.1 Data

(1) Geophysical data

The geophysical data used for the study mainly comprised land use and meteorological data. A dataset on land use covering 5 years (1988, 1995, 2000, 2005, and 2008) which was developed by the Chinese Academy of Sciences, was used for this study (Liu et al., 2003). Land use data were interpreted from satellite remote sensing data obtained through US Landsat TM/ETM images with a spatial resolution of 30 × 30 m. At a scale of 1:100,000, a total of 25 land cover types, identified from the images, were aggregated into six land use/cover types. Specific meteorological data that included annual precipitation, average temperatures, sunshine hours, and relative humidity were obtained from the China Meteorological Administration.

(2) Socioeconomic data

County-level socioeconomic data for the period 1990–2010 were obtained from the Statistics Yearbook for Hebei. The following factors were considered: crop production, agricultural labor, cultivated land, fertilizer use, electricity for rural use, agricultural machinery, and land use conversion, among which most factors are commonly acknowledge as key input and output factors for the analysis of land eco-efficiency

(Pang et al. 2016). Table 1 presents a summary of descriptive statistics for these variables for all of the counties in Hebei. Data on crop production, agricultural labor, fertilizer use, agricultural machinery and electricity for rural use for the same period were obtained from provincial and county-level statistic yearbooks for Hebei. This dataset was compiled based on data obtained from 149 counties that were selected out of a total of 172 counties in Hebei.

Table 1: Descriptive statistics for county-level variables

Variables	Unit	Obs.	Min	Max
Crop production (*y*)	*Tonne*	745	12275	679916
Agricultural labors (*agrlbr*)	*Person*	745	17504	393973
Electricity for rural use (ElecRurUse)	*10,000 kWh*	745	310	285390
Fertilizer use (*fertUse*)	*Tonne*	745	442	74109
Agricultural machinery (*agrMach*)	*Kilowatt*	745	7.8	2171100
Ratio of cultivated land (*R*)		745	0.0567	0.7340
Landscape diversity (*H*)		745	0.8645	2.2803

(3) Data processing

Applying the 1-km area percentage data approach entailing a combination of multiple sources of geophysical and socioeconomic data, we aimed to investigate the influence of land use conversion on crop production in Hebei. Big data technology refers to data processing and the application of multi-source, multi-scale, and integrated technology within scientific research. Protocols and concepts for the integrative technology on spatial data processing date back to the 1970s and have advanced significantly in recent years. For example, "social pixel" locations, referring to the integration of spatial geophysical data and socioeconomic data to obtain information from multiple sources dates back to the early 1990s (Geoghegan et al., 1998; Deng et al., 2008). A specific application relating to the management of resources and the environment is the development of 1-km area percentage data (Liu et al., 2003; Deng et al., 2010), in which the advantages of raster and vector data are combined in the integration of global or regional multi-source data.

3.2 Stochastic Frontier Analysis

Stochastic Frontier Analysis (SFA) can be used to calculate land eco-efficiency. We established a multi-input and multi-output production function, incorporating the ecological variable as one of the inputs. The translog production function and the Cobb-Douglas production function are frequently applied, and we assumed that for each time period t = 1,…T, the input vectors $X^t \in R_+^N$ generated the output vectors, $Y^t \in R_+^N$.

$$S^t = \left\{ (X^t, Y^t) : X^t \ can \quad produce \quad Y^t \right\} \tag{1}$$

Applying the distance function methodology developed by Shephard (1970), the input distance function was defined as:

$$D_I^t(X^t, Y^t) = \sup\left\{ \lambda : (X^t / \lambda, Y^t) \in S^t \right\} \tag{2}$$

Accordingly, the output vector Y^t was treated as a given, and the input vector X^t was adjusted, provided that the input-output vectors were still technologically feasible. It is noteworthy that $D_I^t(X^t, Y^t) \leq 1$ if, and only if, $(X^t, Y^t) \in S^t$. In addition, $D_I^t(X^t, Y^t) = 1$ if, and only if, (X^t, Y^t) is on the boundary or frontier of technology. Thus, for the observed sample *i*, the following equation was derived from the SFA definition.

$$D_I^t(X_i^t, Y_i^t, t; \alpha, \beta, \gamma, \varphi, \delta, \phi) \exp(v_i - u_i) = 1 \tag{3}$$

where $\alpha, \beta, \gamma, \varphi, \delta, \phi$ are all parameters to be estimated. The stochastic frontier model was completed with the inclusion of the term v_i that captured noise, and u_i was defined as technical inefficiency, where *i.i.d* $v_i^t \sim N(0, \sigma_u^2)$ and $u_i^t \sim N^+(u_i, \sigma_u^2)$. The following model for technical efficiency was constructed:

$$u_i = \tau_0 + Z_{ij} * \tau_j \tag{4}$$

where, Z_{ij} is a vector of explanatory variables associated with technical inefficiency effects, τ_0 is the constant item of the technical inefficiency model, and τ_i is a vector of unknown parameter to be estimated (Battese and Coelli, 1988; 1995).

Equation (3) was subsequently transformed into the following equation:

$$\ln(D_I^t(X_i^t, Y_i^t, t)) = u_i - v_i \tag{5}$$

The distance function was characterized by homogeneity, indicating that normalization of the certain input could be expressed as:

$$\begin{aligned} &D_I^t(X_i^t / x_n, Y_i^t, t) = D_I^t(X_i^t, Y_i^t, t) / x_n \\ &\Rightarrow -\ln x_n = \ln(D_I^t(X_i^t / x_n, Y_i^t, t)) - \ln(D_I^t(X_i^t, Y_i^t, t)) \end{aligned} \tag{6}$$

From equations (5) and (6), the following equation was generated:

$$-\ln x_n = -\ln(D_I^t(X_i^t / x_n, Y_i^t, t)) - u_i + v_i \tag{7}$$

Technical efficiency (TE), defined as the ratio of the observed output to the corresponding potential output, given the production frontier, was subsequently estimated by applying equation (7) as follows.

$$Y_i = f(X_i, \beta)\exp(v_i - u_i) \tag{8}$$

Therefore, the following equation yielded the TE:

$$TE_i = \frac{f(X_i, \beta)\exp(v_i - u_i)}{f(X_i, \beta)\exp(v_i)} = \exp(-u_i) = \frac{1}{D_I^t(X_i^t, Y_i^t, t)} \tag{9}$$

Two additional indicators, the ecological performance indicator (EPI) and eco-efficiency (EE) were included in the study. EPI was defined as the ratio of the distance function values obtained from the production function that with ecological input to that without ecological input. The EPI was obtained as follows:

$$EPI_i = \frac{D_I^t(X_i^t \quad eco, Y_i^t) - D_I^t(X_i^t, Y_i^t)}{D_I^t(X_i^t, Y_i^t)} = \frac{TE_i^t(X_i^t \quad eco, Y_i^t) - TE_i^t(X_i^t, Y_i^t)}{TE_i^t(X_i^t, Y_i^t)} \tag{10}$$

EE was defined as the ratio of the minimum feasible ecological input use to observed ecological input use, conditional on observed levels of other input and outputs (Reinhard et al., 1999).

$$EE_i = \frac{\min.feasible \quad eco\log ical \quad input}{observed \quad eco\log ical \quad input} \tag{11}$$

The output distance function was defined similarly as:

$$D_O^t(X^t, Y^t) = (\sup\{\lambda : (X^t, \lambda Y^t) \in S^t\})^{-1} \tag{12}$$

This function was defined as the reciprocal of the maximum proportional expansion of the output vector Y^t, given input X^t. In light of this condition, either of the two functions could be selected.

Specifically, the ecological input in Hebei was land use conversion, and land inputs comprised all of the cultivated land in this region. Thus, the input and output vectors in Hebei were expressed as follows:

$$X_H^t = (cultivatedarea, landscapediversity, capital, labor, property1, property2, ...)$$

(13)

$$Y_H^t = (cropyield) \tag{14}$$

The following equations were generated by combining Eqs. (13) and (14):

$$\begin{cases} -\ln x_n = -\ln(D_I^t(X_i^t(landscapediversity_i)/x_n, Y_i^t, t)) - u_i + v_i \\ -\ln x_n = -\ln(D_I^t(X_i^t(\text{est.}landscapediversity_i)/x_n, Y_i^t, t)) - \xi_i + v_i \end{cases} \tag{15}$$

For the estimation of land eco-efficiency, we assumed that producers' eco-efficiency would be highest when they used the minimum optimal amount of NPP. The input-oriented production function of an eco-efficient producer was obtained by replacing observed *landscapediversity*$_i$ and u_i with min.*feasible landscapediversity*$_i$ and ξ_i, respectively. Following from Eq. (15), an equation relating to $landscapediversity_i$ and $\min.feasible\ landscapediversity_i$ was formulated. Last, the indicator EE_i was calculated using the following equation:

$$EE_i = \frac{est.landscapediversity_i}{landscapediversity_i} \tag{16}$$

4 Results

4.1 Land use management and landscape biodiversity

Land use management is influenced by land use conversion as well as landscape biodiversity. Our quantitative analysis revealed a decreasing trend for the ratio of cultivated land with increased land use conversion (Fig. 2). Studies on land use conversion have revealed diversity relating to landscape patches as well as landscape types and patterns. Whereas land use conversion impacts an ecosystem via its richness and evenness, the area of each landscape influences the distribution of energy and nutrients that affect species' growth. Therefore, land use conversion has a bearing on ecological significance as well as on land use in a particular region. The impact of land use conversion on crop production could be conveyed and represented as an ecological effect, which is expressed as the direct and indirect effects of economic production that are, in turn, associated closely with changes in the cultivated land. Fig. 3 shows that crop production is positively related to the ratio of cultivated land. In sum, a nonlinear relationship exists between land use conversion and crop production. All of these analyses support the view posited in this paper that land use conversion affects crop production in Hebei.

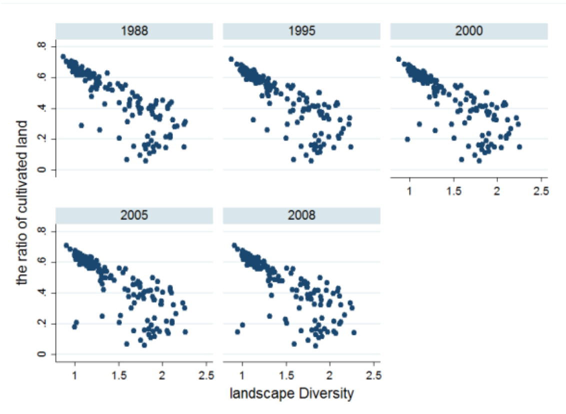

Fig. 2 The relationship between the ratio of cultivated land (R) and land use conversion (Shannon's index, H) in Hebei in 1988, 1995, 2000, 2005, and 2008

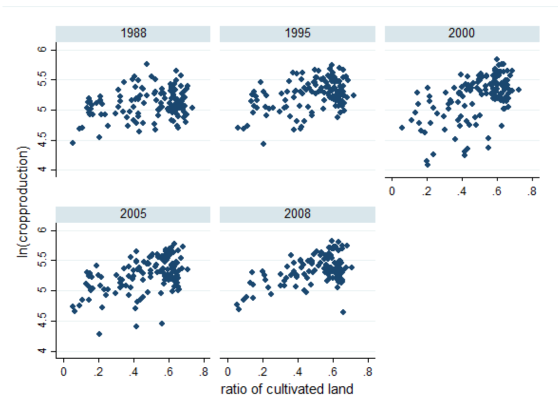

Fig. 3 The relationship between the ratio of cultivated land (R) and crop production in Hebei in 1988, 1995, 2000, 2005, and 2008

Fig. 4 depicts the overall effects of land use conversion on crop production. Two types of impacts relating to land use conversion can be differentiated. The first type of impact is ecological, as land use conversion can result in biodiversity loss and ecosystem degradation. The second type relates to landscape change, which is regarded as a critical factor affecting crop production. This type is represented as variations in Shannon's index, which are closely associated with changes in the area of cultivated land.

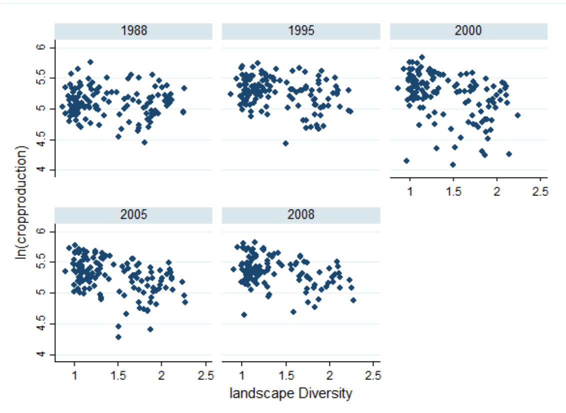

Fig.4 The overall effects of land use conversion (H) on crop production in Hebei in 1988, 1995, 2000, 2005, and 2008

The model for evaluating the effect of land use conversion can be expressed as:

$$\begin{aligned} \ln y_{it} &= 1.4442 + 0.757 \ln agrlbr_{it} + 0.2718 \ln ferUse_{it} \\ &+ 0.0549 \ln EleRurUse_{it} + 0.0082 \ln agrMach_{it} \\ &+ 0.0248 R_{it} + 7.96665 H_{it} - 2.2388 H_{it}^{2} \end{aligned} \quad (17)$$

where y_{it} denotes crop production, $agrlbr_{it}$ denotes agricultural sector employees, $fertUse_{it}$ denotes total fertilizer use, $EleRurUse_{it}$ denotes electricity consumption in rural areas, $agrMach_{it}$ denotes the total power of agricultural machinery, R_{it} denotes the ratio of cultivated land (within a 0–1 range), and H_{it} denotes land use conversion (Shannon's index, H).

As indicated in equation (17), land use conversion contributes significantly to crop production and could be regarded as a landscape-induced ecological effect. Notably, the effects identified by the magnitude of the estimated elasticity are quite small, further indicating that the potential contribution of land use conversion associated with ecological effects to crop production is marginal.

4.2 Analysis of eco-efficiency

Table 2 shows land eco-efficiency values for 11 cities in Hebei that were calculated based on the SFA. The non-constrained results obtained using the SFA model were found to be more scientific expressions of land eco-efficiency in Hebei than those obtained with the constraint model. We can conclude that on average, the land eco-efficiency of cities in Hebei fall within a range of 0.60 and 1.00, with most cities, including Xingtai, Shijiazhuang, Cangzhou, Zhangjiakou, Langfang, and Handan remaining within a range of 0.80–0.95. Land eco-efficiency in Hengshui, Chengde, and Tangshan was relatively high at values above 0.95, whereas land eco-efficiency values for Baoding and Qinhuangdao were comparatively low at just 0.64 and 0.77, respectively. EPI values across cities in Hebei were all positive, indicating that the loss of vegetation contributed significantly to urbanization and socioeconomic development.

The results for the distribution of land eco-efficiency showed that excessive consumption of ecological resources did not occur during the urbanization process in

Hebei. The distribution of land eco-efficiency followed an ‘A’ type rule indicating a steady decrease in eco-efficiency from its peak value moving from east to west (Fig.5).

Table 2: Land eco-efficiency in Hebei based on Stochastic Frontier Analysis

Code	City	Eco-efficiency	EPI
1	Shijiazhuang	0.8436	0.1854
2	Chengde	0.9803	0.0201
3	Zhangjiakou	0.9053	0.1046
4	Qinhuangdao	0.7753	0.2898
5	Tangshan	0.9994	0.0006
6	Langfang	0.9277	0.0779
7	Baoding	0.6419	0.5579
8	Cangzhou	0.8734	0.1450
9	Hengshui	0.9536	0.0487
10	Xingtai	0.8069	0.2393
11	Handan	0.9309	0.0743

Data source: Hebei Statistic Yearbook, 2008.

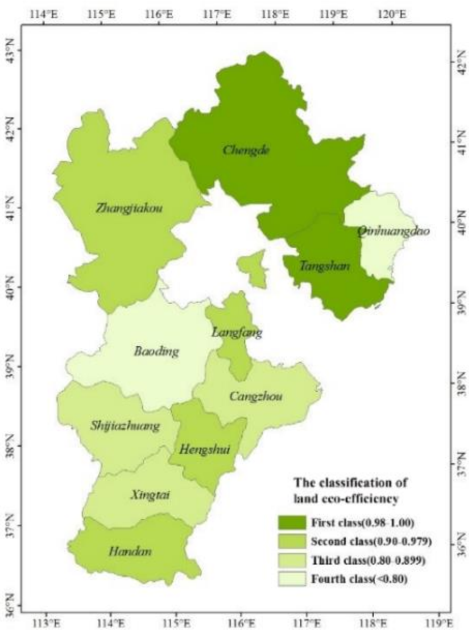

Fig. 5 The distribution of land eco-efficiency in Hebei in 2008

Land eco-efficiency values were found to be consistently high in cities close to provincial or economic centers, or in those located within ecological tourism circles. Conversely, cities located at considerable distances from the provincial center, or those with underdeveloped traffic systems, consistently demonstrated relatively low land eco-efficiency values. Land eco-efficiency is an important indicator of the degree of efficient use of natural goods and services within economic activities. It can be improved by reducing environmental impacts and the use of natural resources while maintaining or increasing the value of the produced output. In other words, land eco-efficiency requires the production of more desirable outputs, such as the gross domestic product (GDP), along with a simultaneous reduction in the consumption of resources and adverse ecological impacts. To conclude, measurements of land eco-efficiency should include a consideration not only of environmental efficiency but also of resource efficiency.

5 Conclusions and Discussion

The contributions of this study lie in its attempt to quantitatively measure and determine the direct and indirect impacts of land use management on crop production by using Shannon's index and to clarify land eco-efficiency condition and its relationship with land use management in Hebei based on SFA.

Land use management influences crop production in two ways: through its impacts on landscape diversity and through land use conversion. To identify explicit interactions of land use management and crop production, independent variables in relation to crop production, including agricultural labor, the ratio of cultivated land, agricultural machinery, fertilizer use, electricity for rural use, and land use conversion were selected for the years 1988, 1995, 2000, 2005, and 2008. Impacts on landscape diversity were directly reflected in Shannon's index, and impacts on land use conversion were reflected in changes in cultivated land caused by its conversion to other uses and vice versa. Ecological impacts induced by land use conversion were found to be positively associated with crop production. Environmental variations in landscapes, including precipitation and soil quality, could also affect crop production. For instance, land use conversion leads to variations in carbon sequestration in soils and in the climate, with long-term changes eventually impacting on crop production.

Changes in cultivated land and crop production are not linearly related. Cultivated land is a key factor affecting crop production, which is positively correlated with crop yields. Whereas a certain amount of land use conversion in relation to crop production is beneficial, conversion beyond a specific range is detrimental. However, enriching biological diversity, which enhances competition between pests and natural enemies, should be prioritized in land use conversion. Thus, advantageous aspects of land use conversion should be considered in relation to crop production. Agricultural inputs such as agricultural machinery, fertilizer, and electricity could also increase crop production. Consequently, strengthening infrastructure also affords a feasible and practical means of advancing crop production.

Land eco-efficiency is an effective indicator of sustainable land use management. Land eco-efficiency of 11 cities of Hebei was calculated based on SFA, which showed that there existed differences in the land eco-efficiency across cities, with consistently high values in cities close to provincial or economic centers, or in those located within ecological tourism circles. With the ongoing need to explore low-carbon development modes, land eco-efficiency should be improved, and key technologies in major areas should be applied to ensure that urban development fits the requirements of ecological civilization. The land use structure and its spatial dimensions should be planned rationally to improve land eco-efficiency and advance sustainable development, which will not only result in improved land use but will also contribute to safeguarding the environment for a sustainable society. In this study, SFA is a useful tool to measure land eco-efficiency, however, there still exists some shortcomings in the application of SFA, including the difficult precise specification of error structure, or the high rick to impose a priori assumption on the production technology. A more advanced method and more detailed database would be helpful to improve further research to support sustainable land use management.

Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This work was financially supported by National Natural Science Fund for Distinguished Young Scholar (Grant no.71225005), National Natural Science Foundation of China (Grant No. 41771568), and the National Natural Science Foundation of International/Regional Cooperation and Exchange Programs (Grant No. 71561137002).

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Chapter 5: Quantitative Measurements of the Interaction Between Net Primary Productivity and Livestock Production in Qinghai Province

This paper has been published in the *Journal of Cleaner Production* 142, 758–766.

Abstract

The interaction between livestock production and net primary productivity (NPP) in Qinghai Province, China, is estimated using simultaneous equations. The total value of livestock production and NPP positively influence each other, so livestock farming in Qinghai Province is not necessarily injurious to vegetation in this region. There is a weak positive effect on NPP of a county-level region having a nature reserve. There are positive effects of temperature, sunshine hours, relative humidity and rainfall on NPP, and therefore indirectly affect livestock production. Higher grazing density negatively affects NPP, so appropriate grazing density and establishing natural reserves are practical actions to sustain livestock farming.

Keywords: livestock production; NPP; grazing density; natural reserve; Qinghai Province

1 Introduction

Livestock production is one of the most widespread human activities; 30% of global land is farmed for herbivores for livestock products (Havlík et al., 2014). Besides, rising prosperity, growing populations, and dietary change lead to increasing demand for meat and milk, particularly in developing countries (Alkemade et al., 2013). Global demand will rise 70 percent to feed a population projected to reach 9.6 billion by 2050. Yet the grassland that sustains livestock farming is declining and is threatened by degradation and climate change (Herrero et al., 2015). Most high-quality natural grassland has been converted to cultivate crops, mixed farming or other land-use types (Conant et al., 2010). While extensive grazing provides an opportunity for maintaining livestock production, it also provides a challenge since grazing poorer rangeland aggravates the decline of grassland. Moreover, climate change including changes in temperature, precipitation and sunlight hours influences grassland productivity and livestock carrying capacity through effects on the growth of vegetation. These effects may be especially for fragile ecosystems, including the Qinghai-Tibetan Plateau (Qian et al., 2013).

Qinghai Province is located between 31°40'- 39°19'N and 89°35′-103°04'E in the northeast of Qinghai-Tibet Plateau (Fig. 1). It is the fourth largest of China's sub-national units, and considered as a fragile ecological environment and has experienced slow social and economic development. It borders Gansu, Sichuan, Tibet and Xinjiang province, and has an area of 7.2×10^5 km^2–. Annual precipitation ranges from 50mm to 450mm and rises as one moves east. Average temperatures range from -5.7 ℃ to 8.5 ℃ and the total solar radiation is 690.8 to 753.6 kJ. Extreme weather events like drought, hail, frost, snow and wind are quite frequent.

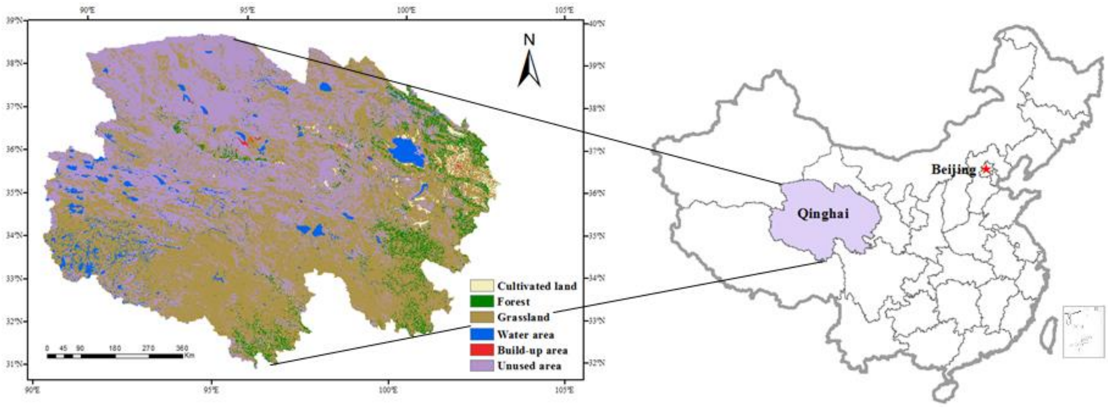


Fig.1 Geographical location and land use/cover pattern in 2008 of Qinghai Province of China.

With an extensive area of grassland, livestock production is a major industry in Qinghai Province. The area for livestock grazing totals 31.6 million hectares, and along with grassland set aside for ecological aims, such as natural reserves, accounting for 51% of the total land area. The main livestock products are beef and mutton, milk and dairy products and wool; Qinghai Province is one of the major wool-producing regions in China. The prosperity and production security of the livestock industry is closely bound up with the quality of pasture. So this paper uses simultaneous equations to quantitatively measure interaction between livestock production and net primary productivity (NPP) in Qinghai Province. The research relies on data fusion techniques to form the spatially detailed NPP measures based on satellite remote sensing, which are linked to county-level data on livestock production.

2 Literature review

2.1 Overview of the impact of climate change on net primary productivity

Net primary productivity (NPP) is the net amount of carbon captured by land plants through photosynthesis (Vorosmarty and Schloss, 1993). It is a key ecosystem carbon cycle parameter, thus linking it to global change (Ruimy et al., 1994). Prior research found that climate change affected the NPP of the world's terrestrial ecosystems, which mattered to agriculture since most of our food depends on growth of vegetation (Melillo et al., 1990). From 1982 to 1999 global terrestrial NPP increased as a result of climate (Nemani et al., 2003), but this was followed by a drought induced reduction from 2000 to 2009 (Zhao and Running, 2010). Overall, the impact of climate change on NPP was ambiguous due to its complexity (Churkina and Running, 1998; Cao and Woodward, 1998).

Temperature, precipitation, radiation and other factors affect the dynamics of NPP and understanding these driving forces may help find constraints on, and effective measures for, sustainable resource management. For example, a terrestrial biosphere simulation model found a 30% reduction of terrestrial NPP over Europe due to a deficiency of rainfall and extreme summer heat (Ciais et al., 2005). Similarly, Qi et al. (2010) found that reduced precipitation and arid climate caused the decline of NPP in the Naqu grassland of Tibet. In addition, based on the CASA (Carnegie-Ames-Stanford Approach) model, Zheng et al. (2013) found that air temperature was a vital driving force for grassland NPP, in their study of Qinghai Lake region during 2000-2010. In summary, the changes of NPP affected by climate elements are tightly related with the growth of vegetation, which in turn is associated with livestock rearing.

2.2 Relationship between net primary productivity and livestock production

Studies in the past decade showed a complex relationship between NPP and livestock production (Milchunas and Lauenroth, 1993; Anadón et al., 2014). On one hand, NPP was the key attribute of grassland carbon cycle and energy flux, with ambiguous impacts on livestock production (Pineiro et al., 2006). Oesterheld et al. (1992) studied managed rangelands in Argentina and found managements influenced the changes of livestock production that was closely associated with NPP. This research approach used NPP as an index to measure the ecosystem's production capacity of dry matter, which was needed for livestock rearing (Monterroso Rivas et al., 2011).

On the other hand, the effects of grazing on NPP, in general, are negative (Wright, 1990; Heitschmidt, 1990; Oesterheld et al., 1999), despite a few of studies having positive effects (Frank and McNaughton, 1993; Altesor et al., 2005). Oesterheld et al. (1992) noted that pressure of grassland for grazing was ten times higher than that in the wild. Since it was projected that global output of livestock, especially meat production, would be doubled by 2050, the pressure of grazing would threaten the environment and pose challenges for grassland productivity (Steinfeld et al., 2006). Wang et al. (2013) modeled NPP with a spatial panel model (for 1986-2009), using climatic and socioeconomic variables, and concluded that diverse polices for sustainable development of grassland were needed to produce a positive relationship between NPP and livestock production. Pineiro et al. (2006) found that livestock grazing across the Rio de la Plata grasslands over the past 370 years affected dynamics of NPP negatively.

2.3 Data fusion technique

We analyze the interaction between net primary productivity and livestock production in Qinghai Province using big data techniques. Data fusion, which was been regarded as a crucial big data technique and originated in the 1970s, could be seen as the foremost attempt for scientific research with multi-source and multiscale data (Waltz and Llinas, 1990; Hall and McMullen, 2004). Socializing the pixels realized the integration of spatial data with multi-source socio-economic data (Geoghegan et al., 1998). A further development was 1-km area percentage data technology, developed in the 1990s to satisfy the demand for the mass storage of resource and environmental data (Liu et al., 2003, 2005; Deng et al., 2010). This technique achieved the positioning of global or regional multi-source data and integrates the advantages of the grid data with vector data.

Big data technique has also been widely used in model-based analyses. Deng et al. (2008) studied the spatiotemporal characteristics of land conversions between forests and other land use/land cover, and between forest cover types, using a 1-km area percentage data model (APDM). Similarly, Zhuang et al. (2002) disaggregated population at county levels to one square kilometer cells across China, while Doll et al. (2000, 2006) mapped regional economic activity from night-time lights observed using satellite. These examples show that data fusion techniques are widely and so also used in the current research. Additionally, we integrate the advantages of grid data with vector data, combining multi-scale and multi-source geophysical data with socio-economic data, in order to explore the interaction between net primary productivity and livestock production in Qinghai Province.

3 Data and methods

3.1 Data

The econometric model used to explore linkages between livestock production and NPP in Qinghai Province relies on geographic data, socio-economic data and indicators of protected areas. These multi-source data during 1990-2010 may originally be at different spatial resolutions but are integrated to county-level in this study. Descriptive statistics for the variables are in Table 1.

Table 1: Data description of the indicators used in the econometric model in this study

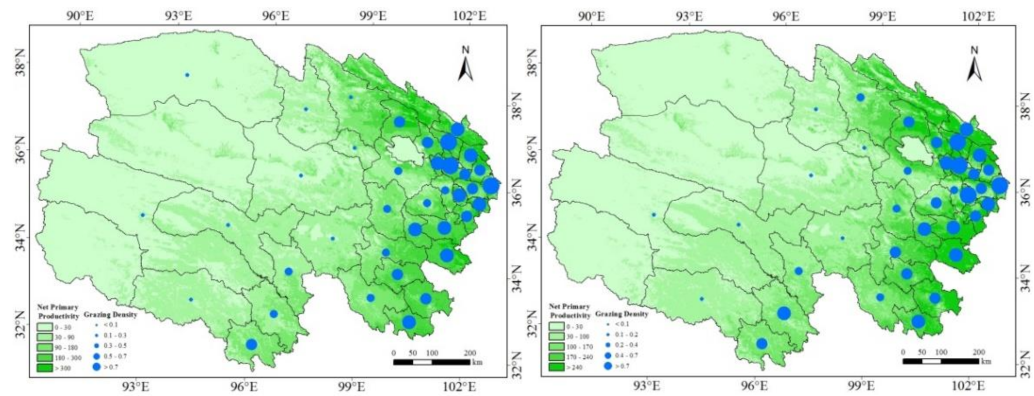
Variable	Unit	Obs.	Mean	Std. Dev.	Min	Max
Value of livestock production (*VLP*)	*10000 yuan*	840	14069	157453	27	4486616
Net primary productivity (*NPP*)	*g.C/km*^{2}	840	173	100	1.7112	366.7946
Gross domestic product (GDP)	*10000 yuan*	840	64687	143331	1324	2000645
Animal (*animal*)	*head*	840	137319	134273	650	2663300
Meat production (*meat*)	*ton*	840	8360	63538	530	1819180
Agricultural labors (*agrilbr*)	*person*	840	33342	40404	300	219540
Grassland(S_g)	*hectare*	840	942673	1150064	48926	5474706
Grazing density (*gden*)	*head/hectare*	840	0.3597	0.3311	0	2.4676
Annual precipitation (*rain*)	*0.1 mm*	840	3987	1221	1372	7655
Temperature (*tem*)	*ºC*	840	2.4670	2.9058	-4.2492	8.9854
Sunshine (*sun*)	*0.1 hours*	840	743	59	586	892
Relative humidity (*ur*)	*%*	840	55	6	36	66
Reserves (*reserves*)	-	840	-	-	0	1

3.1.1 Geographic data

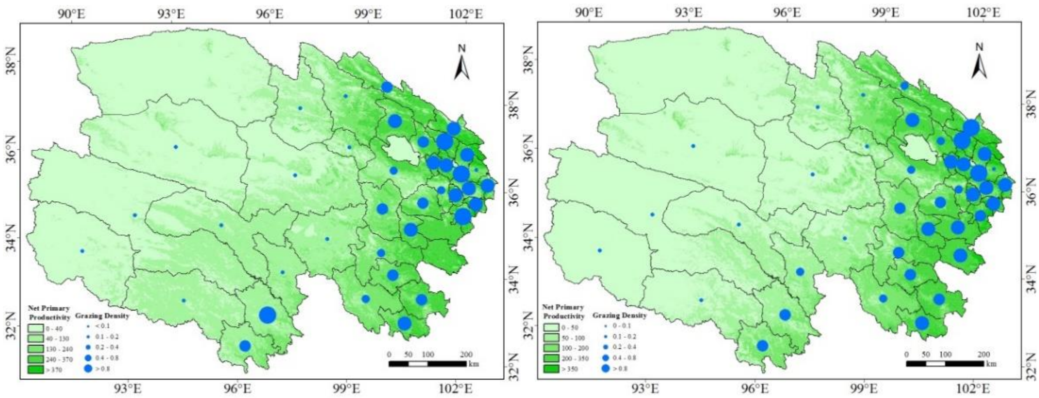
The geographic data mainly includes land-use/land-cover data and meteorological data, especially including the area of grassland, annual precipitation, average temperature, sunshine hours, and the relative humidity. Land-use/land-cover data from the Data Center of the Chinese Academy of Sciences are derived from Landsat Thematic Mapper (TM)/ Enhanced Thematic Mapper (ETM) images in 1988, 1995, 2000, 2005 and 2008 at a scale of 1:100,000. Field survey and random sample check is used to assess the accuracy of the database. The accuracy of the six classes of land use is above 94.3% (Liu et al., 2014). These data recognize six broad land-use/land-cover types: built-up area, cultivated land, grassland, forest area, water area and unused land (Fig. 1).

3.1.2 Socio-economic data

The value of livestock production, gross domestic product (GDP), farm animal numbers, and agricultural labours at county level during 1990-2010 are obtained from the Statistics Yearbook of Qinghai Province. Notably, the Statistics Yearbook of Qinghai Province has 42 administrative regions, including 30 counties, 7 autonomous counties, 3 county-level cities (separated the Delhi city from Ulan county), Qinghai Lake county and municipal district of Xining city. The value of livestock production is used as one endogenous variable, which depends on NPP, GDP, meat production, grazing density, agricultural labors, and natural reserves (natural reserves are settled in order to protect environment by prohibiting livestock activities). Grazing density is calculated as the number of farm animals divided by the Landsat-derived grassland area of each county-level region.



Panel A   Panel B



Panel C Panel D

Fig. 2 Distribution of NPP and grazing density in Qinghai Province in the year of 1995 (panel A), 2000 (Panel B), 2005 (Panel C) and 2010 (Panel D). The grazing activity is concentrated on the area with higher NPP.

3.1.3 Natural reserves

Natural reserves in Qinghai Province have been set up since 2005. They are divided into three kinds of area in terms of protection level: core areas, experimental areas and buffer areas. In general, each type of natural reserve prohibits grazing activities, so we use a dummy variable for whether there is any type of natural reserve in the county-level region.

3.2 Indicators

3.2.1 NPP

NPP is the amount of solar energy converted to chemical energy through the process of photosynthesis (production minus respiration) and represents the primary source of food for Earth's heterotrophic organisms (organisms that require preformed organic compounds for food energy) including human beings. Measures of photosynthetic production—NPP—are useful as a "common currency" for quantifying the impact of land dynamics across a broad spectrum of issues in Earth system science and global change research (Imhoff et al., 2004a; Imhoff et al., 2004b; Imhoff et al., 2006).

The NPP estimates used here are from two sources. First, AVHRR-derived (advanced very high resolution radiometer) NPP is produced by the GLCF (Global Land Cover Facility) research group of the University of Maryland from 1981 to 2000, with 8km×8km spatial resolution, at annual temporal resolution. This NPP ranges from 0 to 1700 $gCm^{-2}year^{-1}$. Second, the MODIS-derived (moderate-resolution imaging spectroradiometer) NPP is from the remote sensing data product MOD17A3 from EOS/MODIS of NASA (National Aeronautics and Space Administration) from 2000 to 2010. The spatial resolution is 1km×1km, and the original temporal resolution is every 8 days (Zhao et al., 2005).

Since these two kinds of NPP data are derived from different sensors, their consistency needs to be checked (Huete et al., 2011). Based on the overlapping year 2000, we used linear regression equation approach of Zhang et al. (2011):

$$\mathrm{NPP}_{MODIS} = a * NPP_{AVHRR} + b$$

where NPP_{MODIS} is MODIS-derived NPP, NPP_{AVHRR} is the original AVHRR-derived NPP, a is the regression slope coefficient and b is the constant. Using this linear regression equation to normalize AVHRR-derived NPP from 1981 to 2000, we deal with the discrepancy of the range of NPP values from these two different sources.

3.2.2 Grazing density

Grazing density (*gden*) is the number of farm animals per unit of grassland area (Manning et al., 2013). The grassland area (S_g) of each county is calculated from Landsat TM/ETM (Thematic mapper/Enhanced Thematic Mapper) satellite remotely sensed digital images, originally for 30 by 30 m pixels which are here aggregated to county level. The total number of farm animals (*animal*) is reported in the *Statistics Yearbook* for Qinghai Province, and is divided by S_g so that livestock grazing density can be written as:

$$gden = animal/S_g$$

3.3 Modelling

Based on the research reviewed, climate change is one of the main factors influencing the spatio-temporal variation in NPP. Livestock farming is another factor likely to cause changes in NPP, for grassland bearing the whole livestock production system. Therefore, the value of livestock production, the climate factors (precipitation, temperature, sunshine, and humidity), grazing density, and a dummy variable for county-level regions with nature reserves are used as explanatory variables:

$$NPP_{it} = f(VLP_{it}, GDP_{it}, rain_{it}, tem_{it}, sun_{it}, ur_{it}, gden_{it}, reserve_{it}) \quad (1)$$

where NPP_{it} refers to the net primary production in the county-level region i in the year of t, VLP_{it} is the value of livestock production, GDP_{it} is gross domestic product, $rain_{it}$ is the annual precipitation, tem_{it} is the average temperature, sun_{it} is gross sunshine hours, ur_{it} is relative humidity, and grazing density is denoted as $gden_{it}$, and $reserve_{it}$ is a dummy variable that equals 1 when a county-level region has natural reserves. We take the logarithm of each variable (except dummy variable, grazing density and average temperature) to allow unit-free interpretation of regression coefficients:

$$lnNPP_{it} = f(lnVLP_{it}, lnGDP_{it}, lnrain_{it}, tem_{it}, lnsun_{it}, lnur_{it}, gden_{it}, reserve_{it}) \quad (2)$$

In addition to influencing NPP, the value of livestock production in turn relies on NPP. We assert that GDP, grazing density, meat production, agricultural workers are other determinants of the value of livestock production, and a dummy variable for counties with nature reserves, conditional on NPP a higher meat production should increase the value of livestock production, as seen in equation (3):

$$lnVLP_{it} = f(lnNPP_{it}, lnGDP_{it}, lnmeat_{it}, lnarglbr_{it}, lnS_{it}) \quad (3)$$

where GDP_{it} is gross domestic product in county-level region i in year t. $meat_{it}$ is meat production, containing beef, mutton, etc., S_{it} is grassland area, $arglbr_{it}$ is the number of agricultural workers, and $reserve_{it}$ is a dummy variable that equals 1 when a county-level region has natural reserves.

Our interest in estimating equations (2) and (3), is based on the theoretical framework shown in Fig. 3 that traces the various pathways for interaction between livestock production and NPP.

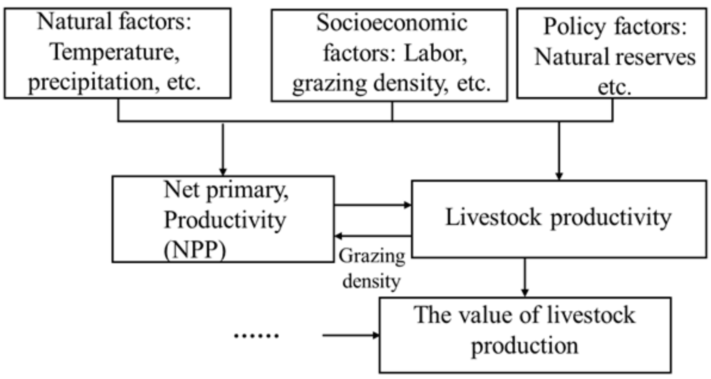


Fig. 3 Analytical framework for exploring the interaction between livestock production and NPP in Qinghai Province.

In order to account for the linkage between the two equations, the Two-stage Least Square (2SLS) method is used to estimate parameters of the models. Thus, model (4) can be expressed as:

$$
\begin{cases}
lnNPP_{it} = \alpha_0 lnVLP_{it} + \alpha_1 lnGDP + \alpha_2 lnrain_{it} + \alpha_3 tem_{it} \\
\quad +\alpha_4 lnsun_{it} + \alpha_5 lnur_{it} + \alpha_6 gden_{it} + \alpha_7 reserve_{it} + \varepsilon_1 \\
lnVLP_{it} = \beta_0 lnNPP_{it} + \beta_1 lnGDP + \beta_2 lnmeat_{it} + \beta_3 lnS_{git} \\
\qquad\qquad +\beta_4 lnarglbr_{it} + \varepsilon_2
\end{cases}
\tag{4}
$$

4 Results

4.1 Interaction between livestock production and NPP

The estimation result of model (4) (Table 2) and its related tests, involving Granger Causality test for panel data (Table 3), autocorrelation test (Table 4), Hausman test (Table 5) and identification test (Table 6) are given. Granger Causality test indicates that there is an interaction between NPP and livestock production. Autocorrelation test shows that lag variable of NPP and livestock production should be incorporated in model (4). Most important, under identification tests of both equations in model (4) indicates that null hypothesis—there is a under identification problem—should be rejected with p values are zero. And over identification test indicates that null hypothesis—instruments are valid for employment—fails to reject. In summary, all these tests show that model (5) is stable and performs well.

The relationship between the value of livestock production and NPP is positive (Fig. 4), and it is still statistically significant once other variables are included in the model, as seen in Table 2 and equation (5). Thus, the development of livestock farming affects NPP to some extent, but sustaining the environment, at least in terms of NPP, can promote livestock production (If NPP of last year is 1% higher, it will contribute to 0.23% of the increase of livestock production).

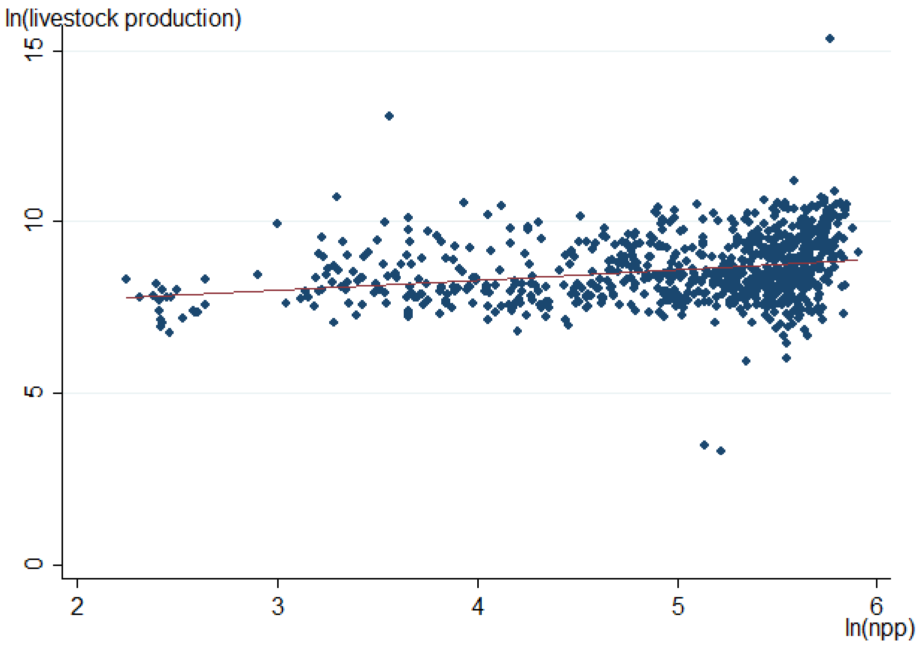


Fig. 4 Relationship between NPP and livestock production of Qinghai Province during 1990-2010.

Table 2: Estimation results of simultaneous equation model for identifying the interaction between livestock production and NPP in Qinghai Province.

variables	Equation (1')	variables	Equation (2')
Independent variable: *ln(NPP)*		Independent variable: *ln(VLP)*	
ln(VLP)	0.03	*ln(NPP)*	0.49
	(1.65*)		(1.28)
ln(rain)	0.06	*ln(meat)*	0.16
	(2.21**)		(2.8***)
ln(sun)	0.80	$ln(S_g)$	-10.31
	(7.45***)		(-2.80**)
ln(ur)	0.62	*ln(agrlbr)*	-0.09
	(6.42***)		(-1.55)
tem	0.09	*ln(GDP)*	0.11
	(13.71***)		(2.17**)
gden	-0.01	$ln(LVP_{i,t-1})$	0.24
	(-1.42)		(3.33***)
reserve	0.06	$ln(LVP_{i,t-2})$	0.15
	(5.64***)		(2.1**)
ln(GDP)	0.04	$ln(LVP_{i,t-3})$	0.08
	(4.04***)		(1.34)
$ln(NPP_{i,t-1})$	0.24	$ln(NPP_{i,t-1})$	0.66
	(3.71***)		(3.99***)

Table 3: Granger Causality Tests

Null Hypothesis		lag(1)	lag(2)	lag(3)	lag(4)	lag(5)
NPP does not Granger Cause livestock production	W	1.51	3.34	5.13	6.15	9.07
	P	0.18	0.02	0.02	0.39	0.75
		-	reject	reject	reject	-
Livestock production does not Granger Cause NPP	W	4.27	5.63	6.19	7.00	8.72
	P	0.00	0.05	0.00	0.08	0.87
		-	reject	reject	reject	-

Table 4: Wooldridge test for autocorrelation in panel data

Null Hypothesis		Equation (1')	Equation (2')
No first-order autocorrelation	F	30.36	3.904
	P	0.00	0.06
		reject	reject

Note: Here we list first-order autocorrelation. The Arellano-Bond estimation also shows that, equation 3' exists third-order autocorrelation, when we add $LVP_{i,t-2}$, $LVP_{i,t-3}$, the model also performs well.

Table 5: Hausman test for NPP model

	(b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ln(livestock)	0.03	0.002	0.03	0.01
ln(rain)	0.06	0.17	-0.10	-
ln(sun)	0.80	0.99	-0.19	-
ln(ur)	0.62	0.88	-0.26	-
tem	0.09	0.15	-0.05	-
gden	-0.01	-0.03	0.01	-
ln(GDP)	0.04	0.01	0.03	0.01
reserve	0.06	0.03	0.030	0..01
ln(NPP)(1)	0.24	0.99	-0.74	0.04
	chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)= 328.34			
	Prob>chi2 =0.00			

Note: The result of Hausman test indicates that fixed effects model should be used here. Livestock production model also uses fixed effects model based on Hausman test, and the test isn't listed here.

Table 6: Under identification test and over identification test of estimation results of simultaneous equation model in Table 2

		Equation (1')	Equation (2')
Under identification	Kleibergen-Paap rk LM statistic	68.75	104.85
	p-value	0.00	0.00
Over identification	Hansen J statistic	8.57	4.35
	p-value	0.13	0.50

$$\begin{cases} lnNPP_{it} = 0.03lnVLP_{it} + 0.06lnrain_{it} + 0.80lnsun_{it} + 0.62lnur + 0.09tem_{it} \\ \quad -0.01gden_{it} + 0.06reserve_{it} + 0.04lnGDP_{it} + 0.24\mathrm{lnNPP}_{i,t-1} \\ lnVLP_{it} = 0.49lnNPP_{it} + 0.16lnmeat - 10.31lnS_{git} - 0.09lnarglbr_{it} + 0.11lnGDP_{it} \\ \quad +0.24lnVLP_{i,t-1} + 0.15lnVLP_{i,t-2} + 0.08lnVLP_{i,t-3} + 0.66lnNPP_{i,t-1} \end{cases} \tag{5}$$

That NPP is increasing with higher valued livestock production is perhaps a surprising result. There is no doubt that farm animals fed on plants affect herbage growth associated with NPP and the negative effect on NPP of grazing density, conditional on the value of livestock production, shows this (Table 2). Yet grazing activity often concentrates on the county-level region with higher NPP (Fig. 2). By and large, they suggest that the livestock industry in Qinghai Province may be further developed without necessarily harming NPP (contribution of livestock production to NPP is 3% while grazing density is -1%, thus restorability of grassland in Qinghai Province is strong enough to bear livestock farming at the moment).

4.2 Potential effects of climate change on livestock production

Climate factors have significant effects on NPP that are precisely estimated (all are p<0.05). Higher rainfall and humidity, and more sunshine all log-linearly associate with higher NPP, while there is a linear effect of temperature, suggesting hotter is always better (Fig. 5). The positive effect of NPP on livestock production also means that these climate effects are similarly positive, so in this case the transmission mechanism may see a positive impact of climate change on livestock production.

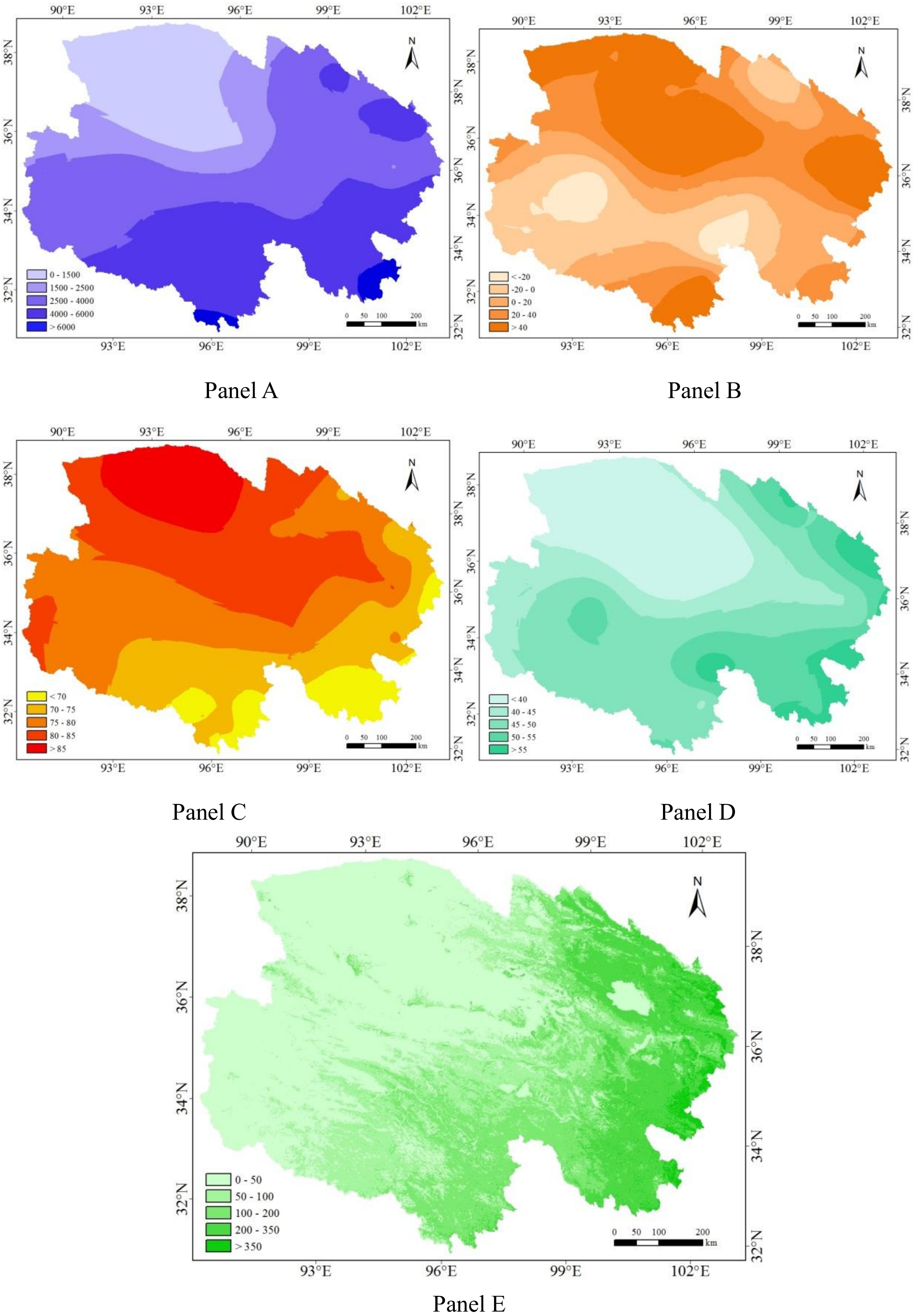


Fig. 5 Maps of the distribution of annual precipitation (panel A), average annual temperature (panel B), sunshine hours (panel C), relative humidity (panel D) and NPP (panel E) in Qinghai Province in the year of 2010.

4.3 Potential effects of establishment of natural reserve on livestock production

The presence of nature reserves within a county-level region is included as a dummy variable to test the hypothesis that ecological projects have a significant impact on NPP and an indirect impact on livestock farming. The results show that, all else the same, NPP is about 6% higher in a county-level region with a nature reserve, and the effect is very precisely estimated (p<0.01). Thus there is likely to be only a marginal, indirect, effect of nature reserves on the value of livestock production, operating via NPP.

5 Conclusion and discussions

5.1 Conclusion

This paper quantitatively analyzes and presents the interaction between NPP and livestock production based on the multi-source data during 1990 to 2010 in the case study area of Qinghai province. In this study, the value of livestock production, the climate factors (precipitation, temperature, sunshine, and humidity), grazing density, and a dummy variable for county-level regions with nature reserves are used as explanatory variables for NPP by applying Two-stage Least Square regression analysis. Through the analysis, it shows that the relationship between the value of livestock production and NPP is positive, and it is still statistically significant once other variables are included in the model, indicating that *NPP does not seem to be traded off for livestock production at current stocking levels*; while climate factors, and the presence of natural reserves are also found to have significant effects on NPP.

The study concludes that variation of NPP goes the same way as changes in livestock production while the grazing activity has an opposite impact on NPP. That indicates that it is still possible for Qinghai province to enhance the livestock production with improved NPP on conditional of the current stocking density is warranted in the context of ecological restoration. Moreover, climate change is also an important aspect for altering NPP, linking to livestock production. In addition, the dummy variable, denoted as natural reserve construction, is useful for illustrating the effect of ecological projects on livestock production transmitted by its function on NPP.

5.2 Discussions

Despite relationships among climate change, NPP and livestock production being examined in several case studies, the literature on the interaction between NPP and livestock production by simultaneous equation modeling is seldom touched. Through this empirical case study, we find that both livestock production and NPP could be improved simultaneously on regional extent, which signifies that the livestock industry can be further developed in conjunction with advocating ecological conservation in Qinghai province, as seen by the positive relationship between the value of livestock production and NPP. This conclusion differs from most of the research on NPP and livestock production.

This research finds that NPP moves together with livestock production while opposite to the tendency of grazing density. Thus, the livestock industry in Qinghai province can be further supported without limiting the priority for ecological preservation. Specifically, climate change affected livestock production via acting on variations of NPP, and the construction of natural reserves appears to be beneficial to livestock production even though it prohibits grazing. In addition, a full system of equations can encompass more endogenous variables by adding more equations for a further exploration on the interaction between variations in NPP and in livestock production.

Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This research was financially supported by the National Key Programme for Developing Basic Science (Grant No. 2012CB955700), the National Natural Science Funds of China for Distinguished Young Scholars (Grant No. 71225005), and the Key Project in the National Science & Technology Pillar Program of China (no. 2013BAC03B00).

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Chapter 6: Managements of Trade-offs Between Conversions of Cultivated Land and Changes of Land Productivity in Shandong Province

This paper has been published in the *Journal of Cleaner Production* 142, 767–774.

Abstract

This study aims to analyze the trade-offs between cultivated land conversions and land productivity using data fusion. First, 1-km area percentage data model, which integrates advantages of grid data and vector data, is applied to detect cultivated land conversion in each 1km×1km grid cell in Shandong province. Then land productivity in the study area is assessed with the Estimation System of Land Production (ESLP) based on agro-ecological zones, which integrates multi-source data, including land use data, climatic data, radiation parameters, soil properties. Estimation result shows that the average land productivity of the whole study area is 7509 kg·hm^{-2} during 1985-2010, while land productivity of built-up land and water areas with low vegetation is zero. Furthermore, results of comparative analysis on cultivated land conversion and land productivity shows that land productivity in Shandong province is unevenly distributed, which is higher in the west part of the study area, and lower in the regions where cultivated land conversion occurs. And the overall trend of land productivity is in a decreasing trend during 2003-2010. The measures of management of this trade-off should be focused on preventing cultivated land conversion.

Keywords: land productivity; land use; land conversion; data fusion

1 Introduction

Land resource for cropping is one of the key determinants of agricultural production, and the report released by FAO (2011) has revealed that the increasing population is expected to cause additional 70% increase in global demand for agricultural production with current cultivated land by 2050. It is well known that China's cultivated land area per capita ranked as one of the lowest worldwide, and the second national land survey has showed that the cultivated land area per capita is 913 m^2, less than half of the world average level (FAO, 2009). However, urbanization, economic growth and industrial transformation aggravate land conversion, which incurs the competition between cultivated land and built-up land and imposes an overriding challenge upon the food safety. The problem seems to be particularly distinct in Shandong province, which is one of the major grain production regions in China.

Shandong province is located on the eastern edge of the North China Plain (114°19'-122° 43'E, 34°22'-38°15'N) and at the lower reaches of the Yellow River (Fig. 1). It covers a total area of over 151, 100 km^2, 55%, 15.5% and 13.2% of which are plains, mountainous area and hilly area, respectively. Shandong province lies in the warm-temperate zone with the continental monsoon climate, with the annual mean temperature ranging from 11 to 14 ºC and the annual precipitation ranging from 550 to 950 mm.

Cultivated land conversions may create positive externalities, such as outstanding economic growth, increasing agricultural production through technological innovation and shared information (Bai et al., 2011; Song et al., 2013; Deng et al., 2013a). In Shandong province, gross domestic product (GDP) was 3.12 trillion yuan by the end of 2008, which was 27 times higher than that of 1988 (NBSC, 1999-2009). In the same time, the industrial structure, which is represented by the ratios of primary industry, secondary industry and tertiary industry in the total GDP, changed from 3:4.4:2.6 in 1988 to 1:5.7:3.3 in 2008 (NBSC, 1999-2009). Otherwise, cultivated land conversions generate negative externalities, such as problems in the public safety, health and social equality (Deng et al., 2008; Liu et al., 2014a), and the most significant negative effect is cultivated land loss (Huang et al., 2007; Wu et al., 2011). Along with the changes in industrial structure, there is an obvious land use/land cover change (LUCC) in Shandong province. The built-up land area in Shandong province increased from 34123 km^2 to 39110 km^2 during 1988-2008, but meanwhile the cultivated land area decreased from 83623 km^2 to 80135 km^2 (It is calculated by our own land use dataset used to estimate land productivity). Apparently, the cultivated land loss and built-up land expansion suggest that land conversion is caused by the increasing demand for built-up land, which is at the expense of occupying other types of land (Song and Deng, 2015). However, land resource and other natural resources are translated into food for millions of people (Fader et al., 2013), otherwise, food production exerts pressure on land and other resources (Pfister et al., 2011). Although the grain production in Shandong province had been continuously increasing since 2003, the growth rate shows it decreases. A slowdown of the growth rate of grain supply is primarily caused by land productivity degradation and cultivated land loss (Alston et al., 2009; Smith and Gregory, 2013). On one hand, cultivated land conversion is decreasing the cultivated land area for grain production; on the other hand, cultivated land conversion affects land productivity through changing its properties. As land conversion can be detected with Geographic Information System (GIS) and Remote Sensing (RS) techniques, how can the land productivity be assessed? What kind of strategies should be used to improve or remain land productivity for grain production?

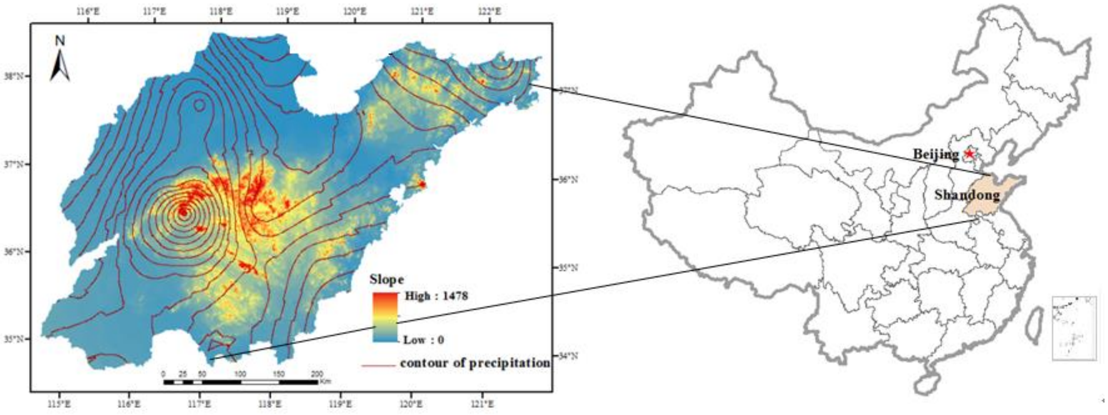


Fig. 1 Location and mean annual rainfall of the study area of Shandong province.

This study answers these questions by exploring the trade-offs between cultivated land conversions and land productivity by using 1-km area percentage data model and Estimation System of Land Production (ESLP). Firstly, literature review shows the context of land productivity and big data technology, with priorities of combining both vector data and grid data. Secondly, this study utilizes 1-km area percentage data model to simulate cultivated land conversion. Thirdly, land productivity is estimated by using ESLP, which integrates multi-source data into different forms of indices to calculate land productivity. Fourthly, cultivated land conversion data and land productivity data in 1km×1km grid cells are compared to analyze their trade-offs. Finally, a concise conclusion is provided.

2 Literature review

2.1 Land productivity

Land productivity refers to the capacity of agricultural land to produce plant biomass under the constraints of each agro-ecological zone (FAO, 2003; Barrios, 2007). Pieri (1995) and Dengiz and Sağlam (2012) defined land productivity as "the condition and capacity of land, including its soil, climate, topography and biological properties, for purpose of production, conservation, and environmental management". Driving mechanism of land productivity should be accordingly clarified before the assessment. Dynamics of land productivity is induced by diverse factors, involving both geographic forces and socio-economic forces (Holden et al., 2001; Datta and De Jong, 2002; Holden and Shiferaw, 2002; Song and Pijanowski, 2014). Barrios (2007) concluded that soil biota directly and indirectly affected land productivity via ecosystem services, which actually referred to provisioning services and natural flow, as it stated that soil organism community had an influence on crop yield and participated carbon and nutrients cycles. Research on soil erosion and land productivity indicated that soil erosion as one of the most serious determinants for degradation of land productivity was often neglected or treated as a loss of infrastructure rather than a loss of production capacity (Bakker et al., 2005; Larney and Janzen, 2012; Power et al., 2014). Documentation of Blaschke et al. (2000) manifested that surface-erosion-induced loss of land productivity emphasized the issue of decreasing crop yield. Aside from the geographic forces for assessing land productivity, the relationship between socio-economic forces and land productivity was widely investigated in the field of economy. For example, Chand et al. (2011) showed that the farm size was closely associated with land productivity. Dyer (1997) argued that land productivity tended to drop in a long run with smaller farms as smaller households intended implement intensive cultivation of land to maintain the labor productivity.

The assessment of land productivity is to obtain the optimal production capability of agriculture for human’s requirement in a certain premise of climate condition, soil property, land-use intensity and management measures (Deng et al., 2013b). Land productivity can be estimated for any unit area, ranging from pixels, plots to countries, and even the global scope (Fischer et al., 2000; Atehnkeng et al., 2008). There are diverse methodologies for assessing land productivity, but a common step is to stepwise correct the target index. Original FAO Agro-ecological Zones Project is an early exercise to apply land evaluation at a continental scale (FAO, 1978). The ESLP assesses land productivity based on the agricultural ecology zone. Compared with other models, ESLP considers substitutability of land use types and crop types, adopts multi-objective programming to evaluate land productivity. Simultaneously, diverse parameters are combined with the input factors and management information in the ESLP to get a result that can be appropriate for sustainable land use (Deng et al., 2009).

2.2 Trade-offs between cultivated land conversions and land productivity

Changes of land productivity are driven by diverse factors. Cai et al. (2010) used land productivity as a mediator to clarify the relationship between land availability and biofuel production, the result of which indicated that land productivity varied with land use/cover change, and urban land scored the lowest and cropland ranked middle of all. This implied that cultivated land conversion in Shandong province, resulting in shrinking cultivated land and sprawling built-up land, might decrease the overall land productivity. Moreover, land productivity is often represented by net primary productivity (NPP) in many studies since NPP is deemed as a proxy for biomass (Haberl et al., 2007; Carreño et al., 2012). With respect to the exploration of NPP and cultivated land conversion, empirical studies of Gingrich et al. (2015) measured the effect of land conversion on NPP based on analysis of the land use change in multiple countries. Their results indicated that land conversion led to a decline in NPP in the early 20th century and growth in the earth 21st century, the increase in NPP mainly happened in regions where agriculture was intensified as well as regions with low coverage forests (Gingrich et al., 2015). Imhoff et al. (2004) studied the influence of urban land transformation on NPP and indicated that urban land encroached agricultural land, which would lead to the loss of NPP. Thus, this hazardous impact makes analysis on cultivated land conversion and land productivity in trade-off system necessary.

2.3 Progress of spatial data format for data fusion

Big data technology, the new mega-rich of Silicon Valley at first, is the master at harnessing data of the Web, such as online searches, posts and messages with Internet advertising (Lohr, 2012). Now, it has become a hot topic across nearly every field of ecology and economy for science research and decision making, and the concept of big data is more extensive including sensors, satellites and so on (Wamba et al., 2015). It is defined as a new-type technology to economically extract valuable information from multi-source and multi-scale data (Gantz and Reinsel, 2012; McAfee et al., 2012). It is an aggregated technology of handling and utilizing a wide variety of data for scientific research, which is now widely used throughout the various research fields including resource management and environmental protection (Dubey et al., 2015; Song et al., 2016). Aside from possessing the advantages of multiple data, the analysis of these data and the presentation of the results are another two features of big data technology (Zikopoulos and Eaton, 2011). Improved access to information is another aspect for fueling big data technology (Madden, 2012). To some extent, big data technology is prior for its merits of mass storage and fusion technologies. For example, the integration of spatial data with socioeconomic data realized the positioning of multi-source information, which is known as “socializing the pixels”, the technology can be dated back to the 1990s (Geoghegan et al., 1998; Deng et al., 2008).

1-km area percentage data technology was prevailing in the 1990s, which integrated the advantages of the grid data and vector data to realize the fusion of global or regional multi-source data and information. It provides successful examples of big data technology for the resource and environment management (Liu et al., 2003; Deng et al., 2010). It is well known that vector data and raster data are two of the most widely used data formats in spatial data analysis (Lin and Kao, 1998; Wicks et al., 2002), and both of them have a number of advantages and disadvantages (Chen et al., 1999). By incorporating the advantages of the two types of data, Liu et al. (2002) developed the prototype of 1-km area percentage data model to realize the identification of the direction and intensity of cultivated land conversion. The framework of 1-km area percentage data model developed by Chinese Academy of Sciences was derived from the concepts of map-algebra, a method for visualization of geographic symbols and spatial analysis by arithmetic of a set of spatial grids (Takeyama and Couclelis, 1997; Mennis et al., 2005).

3 Approach and data
3.1 Approach
3.1.1 1-km area percentage data model

This study analyzes the impacts of dynamics of cultivated land and built-up land on land productivity in Shandong province at the 1km×1km grid scale based on the fusion of socio-economic data and geographic data. The LUCC can be identified on the 1km×1km grid scale, and the 1-km area percentage data model is introduced in this study to trace cultivated land conversions at the 1km×1km grid level. 1-km area percentage data model realizes the detection of cultivated land conversion contains three steps in the ArcGIS software environment. Firstly, as the model is employed to analyze cultivated land conversion in this study, a vector map of land use/cover changes during the study periods at the scale of 1:100,000 is generated at the very beginning. Secondly, cultivated land conversion is uniformly partitioned by forming a 1km×1km FISHNET vector map with an administration boundary of Shandong province, and each cell in the 1-km FISHNET vector map is assigned a unique ID. The third step is to overlay the land use/cover change map with the 1km×1km FISHNET vector map, and LUCC in each 1-km grid can be traced by 1-km FISHNET vector cell IDs in the TABLE module of Arc/Info. Finally, the vector data is transformed into grid raster data after finishing the above operations to identify the conversion direction and intensity. 1-km area percentage data model generates a basic dataset for detecting the encroachment of built-up area onto cultivated land in this study.

3.1.2 Assessment of land productivity

This research estimates land productivity at pixel level based on ESLP. The ESLP is conducted on the basis of agroecological zones through considering common characters that affect crop growth, including the climate conditions, soil properties and other geographic features. Each pixel in agro-ecological zones should be relatively consistent in the aspect of the growth environment and condition. Factors selected to estimate land productivity are in light of literature review in above, then land productivity of each grid is calculated by overlaying the information of land ownership, land suitability, population carrying capacity, etc. The estimation of land productivity can be divided into five steps, namely photosynthetic productivity, light-temperature productivity, climatic productivity, soil productivity, land productivity.

Firstly, photosynthetic productivity is expressed as follows.

$$Y_p = Cf(Q) = K\Omega\mathcal{E}\varphi(1-\alpha)(1-\beta)(1-\rho)(1-\gamma)(1-\omega)(1-d)sf(L)(1-\eta)^{-1}(1-\delta)^{-1}q^{-1}\sum Q_j \quad (1)$$

where Y_p (Unit: kg/hm^2) represents photosynthetic productivity, which refers to the productivity totally determined by photosynthetically active radiation (PAR) with temperature, moisture, soil, crop varieties and other agricultural technical conditions in optimum. C is the unit conversion , K is area coefficient, Ω is the light use efficiency of crops, $\mathcal{E}$ is the ratio of photosynthetically active radiation (PAR) calculated by PAR divided by the total radiation, φ is the conversion efficiency of photon, α is the reflectivity of plant population, β is the transmissivity of flourish plant population, ρ is the ratio of radiation captured by the organs of crop not for photosynthesis, γ is the ratio over light saturation point, ω is the proportion of respiration consumption to photosynthate, d is the abscission rate of cauline leaf of crops. s is economic coefficient of crops, which varies with crop types, natural condition and cultivation technics. $f(L)$ is the modified value of dynamics of leaf area of crops, η is moisture content of mature crops, δ is the ash rate, q (Unit: MJ/kg) is the heat per dry matter, $\sum Q_j$ (Unit: MJ • m^{-2}) is the total solar radiation in crop growth period. Guo et al. (1995) and Sun et al. (1998) provided the methods for evaluating these parameters.

Secondly, Equation (2) presents the light-temperature productivity.

$$Y_{lt} = f(T)Y_p \tag{2}$$

where Y_{lt} (Unit: kg/hm^2) is the light-temperature productivity, which refers to agricultural productivity determined by photosynthesis and temperature condition when moisture, soil, crop varieties and other agricultural technical conditions are in the optimum conditions; $f(T)$ refers to the modified function for temperature, which can be written as follows.

$$f(T) = \frac{(T-T_1)(T_2-T)^B}{(T_0-T_1)(T_2-T_0)^B} \tag{3}$$

$$B = \frac{T_2-T_0}{T_0-T_1} \tag{4}$$

where T (Unit: ºC) represents the average temperature in a certain period, T_0, T_1, and T_2 (Unit: ºC) separately refers to the optimum temperature, lowest temperature, and highest temperature in the course of crop growth. $f(T)$ is the asymmetric parabolic function identified by T, T_0, T_1, and T_2, ranging from zero to one. The crop growth period is divided into five stages, namely seeding stage, vegetative stage, reproductive stage, filling stage and mature stage, and $f(T)$ of each stage is calculated.

Thirdly, climatic productivity can be calculated based on the former two steps, it takes precipitation and irrigation into account.

$$Y_w = Y_{lt}f(W)(1-I) + Y_{lt}I \quad (5)$$

where Y_w is the climatic productivity (Unit: kg/hm^2), I is irrigation efficient, which calculated by irrigated cultivated area divided by total cultivated area. $f(W)$ is modified coefficient for precipitation, which can be rewritten as follows:

$$f(W) = 1 - K(1 - Pe/ET_m) \quad (6)$$

where K is production response coefficient, Pe is the effective precipitation (Unit: mm), and it can be calculated by the model designed by United States Department of Agriculture (USDA) Soil Conservation Service as follows.

$$\begin{cases} \mathrm{Pe} = \frac{\mathrm{R}(125-0.2\mathrm{R})}{125}, & \mathrm{R} < 250 \\ \mathrm{Pe} = 125 + 0.1\mathrm{R}, & \mathrm{R} > 250 \end{cases} \quad (7)$$

where R (Unit: mm) means the total precipitation. ET_m (Unit: mm) is the largest evapotranspiration in crop growth period, which can be calculated with Equation (8).

$$ET_m = K_1 ET_0 \quad (8)$$

where K_1 is crop coefficient, related to season, crop type and crop community structure, etc. ET_0 (Unit: mm) represents the evapotranspiration rate from a reference surface, it is estimated by the improved Penman-Monteith model, which could be rewritten as follows.

$$ET_0 = \frac{0.408\Delta(R_n - G) + \emptyset\frac{900}{T' + 273}u_2(e_s - e_a)}{\Delta + \emptyset(1 + 0.34u_2)} \quad (9)$$

where Δ (Unit: kPa • P^{-1}) is the slope of the saturation vapor pressure-temperature curve, R_n (Unit: MJ • m^{-2} • h^{-1}) is the net radiation of crop canopy surface, G (Unit: MJ • m^{-2} • h^{-1}) is the soil heat flux, which is the energy utilized for heating soil. $\emptyset$ (Unit: kPa • P^{-1}) is the psychrometric constant, T' (Unit: ºC) is the mean daily air temperature, u_2 (Unit: ms^{-1}) is the wind speed at 2 meters height, e_s (Unit: kPa) is the saturation vapor pressure, e_a (Unit: kPa) is the actual vapor pressure, $e_s - e_a$ is the vapor pressure deficit of the air. Additionally, soil heat flux can be calculated by Equation (10).

$$\mathrm{G} = 0.1 \times \mathrm{R}_n \tag{10}$$

Fourthly, soil productivity can be obtained by modifying the climatic productivity (Y_w) with the coefficient of soil availability ($f(S)$).

$$Y_s = f(S)Y_w \tag{11}$$

$$f(S) = \sum_i A_i\, W_i \tag{12}$$

where A_i represents the factors affecting soil availability, i is the number of factors, W_i is the weight of each factor.

Fifthly, we can get the land productivity based on ESLP, which introduces multiple objective analytics to work out land productivity of each grid by using the following equation.

$$Y = f(I_0, Y_s) \tag{13}$$

where I_0 is the total socio-economic investment, and land productivity meets the condition of revenue maximization.

$$f(I, Y_s)P_e - I < f(I_0, Y_s)P_e - I_0, \quad \forall I \neq I_0 \tag{14}$$

$$\begin{cases} f'^{\,(I_0,Y_s)P_e} - 1 = 0 \\ f''(I_0, Y_s) < 0 \end{cases} \tag{15}$$

where P_e is the expected price.

3.1.3 Impact of cultivated land conversion on land production

To distinguish the impacts of cultivated land conversions on land production, we apportioned the contribution of the major variables (including cultivated land area and land productivity) to the total land production as follows:

$$\Delta A = A_2 - A_1 \tag{16}$$

$$\Delta P = P_2 - P_1 \tag{17}$$

where ΔA represents the changes of cultivated land area, A_1 and A_2 are cultivated area in the base year and selected year, respectively; ΔP, P_1 and P_2 are the changes of land productivity, land productivity in the base year and land productivity in a selected year, respectively. As cultivated land area can be extracted from remote sensing data, land productivity can be computed by using ESLP, changes of land production of each 1-km cell can be written as follows.

$$\begin{aligned} \Delta Q &= Q_2 - Q_1 \\ &= A_2 \times P_2 - A_1 \times P_1 \\ &= (A_1 + \Delta A) \times (P_1 + \Delta P) - A_1 \times P_1 \\ &= A_1 \times \Delta P + \Delta A \times P_1 + \Delta A \times \Delta P \end{aligned} \quad (18)$$

where changes of the total land production (ΔQ) was categorized into three parts: (i) changes in land production caused by changes in land productivity ($A_1 \times \Delta P$); (ii) changes in land production resulting from the cultivated land area change ($\Delta A \times P_1$); and (iii) changes in land production under the joint effects of the change of land productivity and change of cultivated land area ($\Delta A \times \Delta P$).

3.2 Data sources

The data used in this study is categorized into geographic data and socio-economic data. The geographic data involves meteorological data, soil properties data and land use/cover data, among which land use/cover data is majorly employed in 1-km area percentage data model. Meteorological data and soil properties data are introduced into ESLP to calculate land productivity (Table 1). Meteorological data, such as temperature, rainfall and radiation are derived from China Meteorological Administration, collected from 117 meteorological stations from 1985 to 2010. Soil property data is derived from the Second National Soil Survey. Additionally, socioeconomic attributes are acquired from Statistics Yearbook of China (NBSC, multiple years). Instead of accessing to traditional statistical databases, the land use/cover data is provided by the Data Center of the Chinese Academy of Sciences. It is interpreted from Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper (ETM) images in the year of 1988, 1995, 2000, 2005 and 2008 at the scale of 1:100,000. Uniform quality control and integration checking was implemented to guarantee the data quality and consistent interpretation, and the overall accuracy of the land use/cover data use in this study is above 94.3% (Liu et al., 2014b). There are six major land use/cover types, i.e., built-up land, cultivated land, grassland, forestry land, water body and unused land, and we extracted the information of built-up land and cultivated land to analyze the relationship between them. Moreover, we select different crop types to calculate land productivity in the light of 25 kinds of land use types, among which paddy land is primarily used for rice, dry land is mainly used for corn, bean, sorghum and millet, and the average productivity of these five crop types was taken as the light-temperature productivity of cultivated land.

Table 1: Indicators used in ESLP to calculate land productivity in this study.

Index type	temperature	rainfall	radiation	Soil	Land use	Other factors
Indicators	Accumulated temperature	Precipitation	Sunshine hours	Soil texture	Land use structure	Wind speed
	Mean daily temperature	Relative humidity	PAR	Soil fertility	Land use intensity	Saturation vapor pressure
	Daily maximum temperature	Precipitation intensity		Erosion intensity		Actual vapor pressure
	Daily minimum temperature	Precipitation variation				

Note: Meteorological data in Table 1 were collected from meteorological stations, related parameters and the other data were calculated based on these indicators.

4 Results

4.1 Spatial distribution of land productivity

4.1.1 Estimation of land productivity

The estimation results from the ESLP show that the spatial distribution of land productivity is uneven in Shandong province (Fig. 2). Obviously, land productivity is higher in the west part of Shandong province and lower in the east part. Besides, the color of land productivity shows a decreasing trend as the built-up land area increases (Fig. 2, 3). In addition, the results show that the land productivity ranged from zero to 13957 kg·hm^{-2} among all pixels, 9.2% out of which show their land productivity is zero, these pixels are often occupied by built-up land or water bodies with very low vegetation coverage (Fig. 3). The average land productivity of the whole study area was 7509 kg·hm^{-2} during 1985-2010, and the land productivity of over 56% of pixels exceeded the average level. In particular, pixels with land productivity ranging from 10000 kg·hm^{-2} to 12000 kg·hm^{-2} accounted for 23.5% of the total area (Fig. 4).

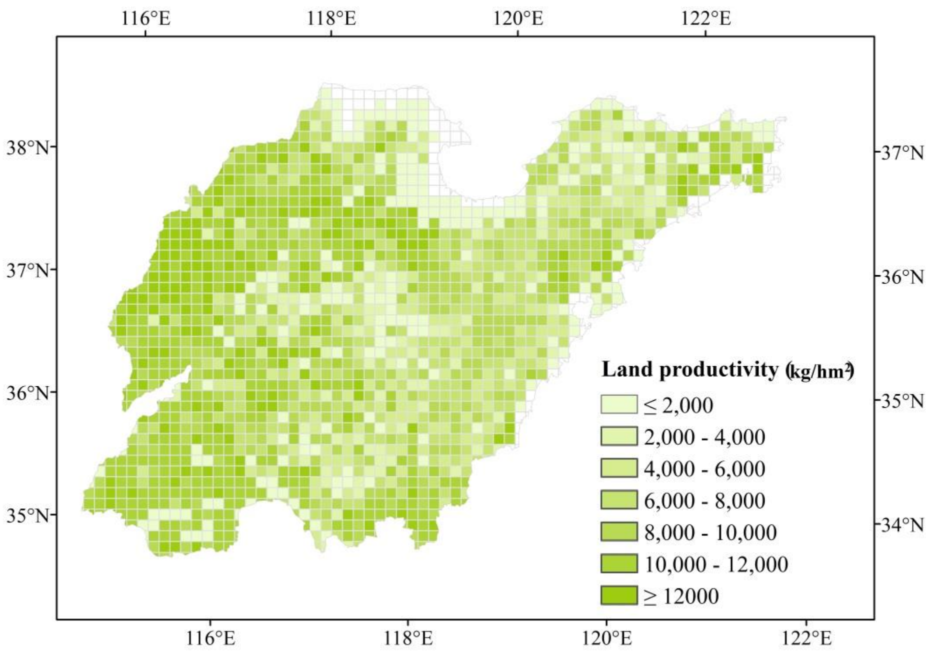


Fig. 2. Estimated multi-year average land productivity based on annual observed data during 1985-2010 in Shandong province

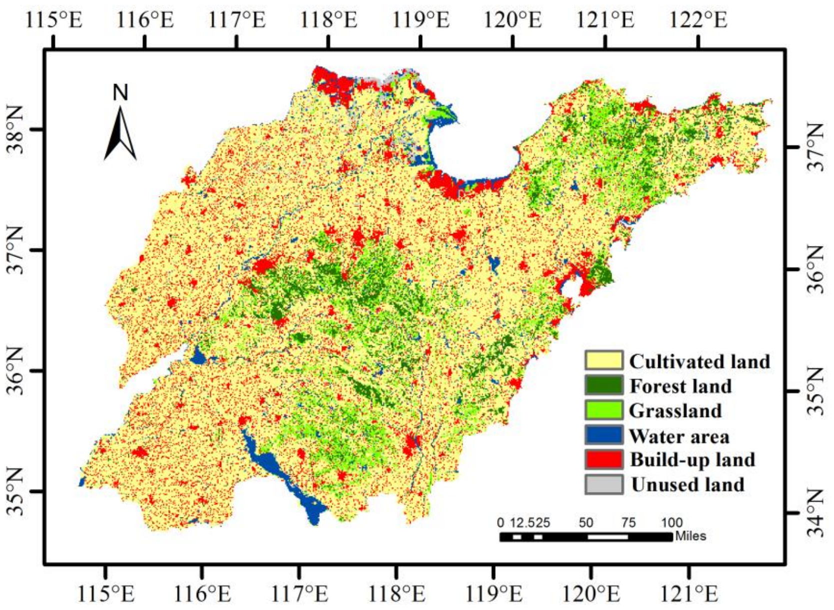


Fig. 3. Land use/cover map of Shandong province in 2008

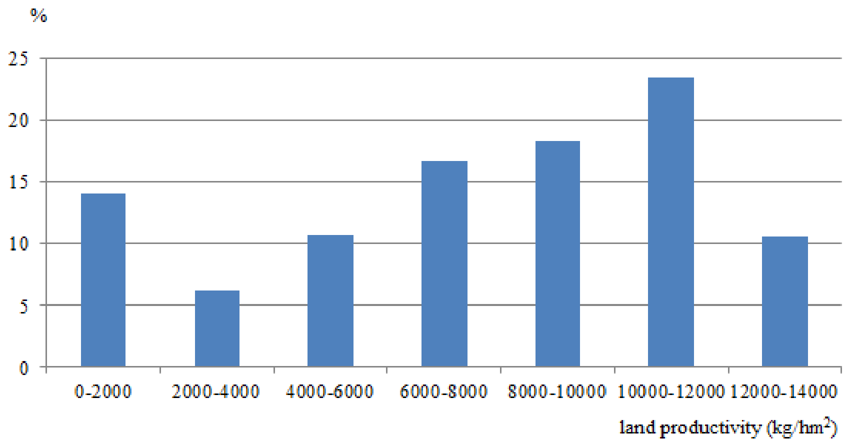


Fig. 4. Interval distribution of multi-year average land productivity during 1985-2010 in Shandong province

4.1.2 Validation of estimated land productivity

The grain yield of 110 counties in Shandong province is incorporated to compare with the average land productivity estimated based on the ESLP. The validation results show that land productivity from the ESLP is significantly correlated with grain yield (R^2=0.63, p<0.01), indicating that land productivity estimated by using the ESLP can be used to represent the agricultural productivity (Fig. 5).

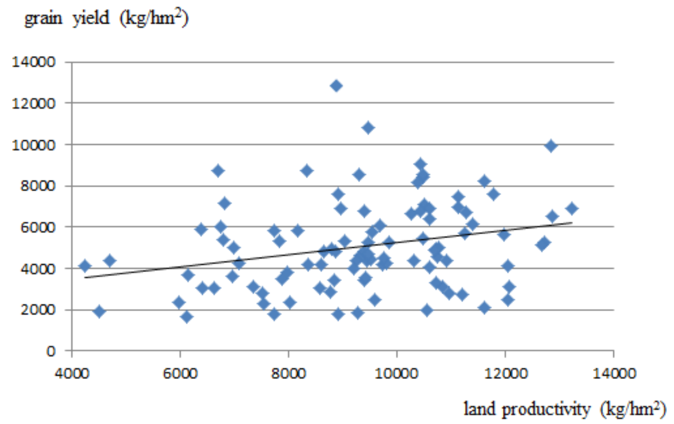


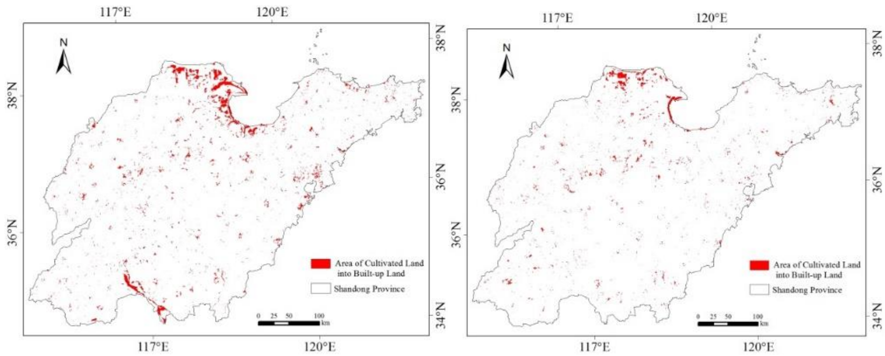
Fig. 5. Relationship between land productivity estimated based on ESLP and grain yield in Shandong province.

4.2 Spatial association of cultivated land conversion and land productivity

In terms of spatial distribution, changes in land productivity and cultivated land conversion in Shandong province shows that expansion of built-up area affects land production (Figs. 2 and 6). As shown in Equation (18), cultivated land conversion is tightly associated with changes in land productivity. Specifically, when cultivated land transforms into built-up area, cultivated land conversion influences the land production through the change of cultivated land area, change of land productivity and their synergistic effects. Additionally, built-up area expands at the expense of decreasing cultivated land area (Fig. 6), even if this trend slows down. Overall, the above analysis apparently proves that land productivity is relatively lower in the regions where cultivated land conversion occurs.

In terms of temporal trend, with Grain for Green Program implemented in 2003, the average land productivity was in a decreasing trend during 2000-2002 (-2595 kg/hm^2) and 2003-2005 (-138 kg/hm^2), respectively. By the same token, during 2005-2008 the land productivity declined by 1612 kg/hm^2 (Fig. 7). Furthermore, there were 137,914.8 hm^2 cultivated land transformed into built-up land during 2000-2005 and

104,729.8 hm^2 during 2005-2008. Therefore, both these findings prove that land productivity declined as the built-up land area increased.



Panel A Panel B

Fig. 6. Land conversions between cultivated land and built-up land: Panel A and B depict the cultivated land transformed into built-up area during 2000-2005 and 2005-2010, respectively

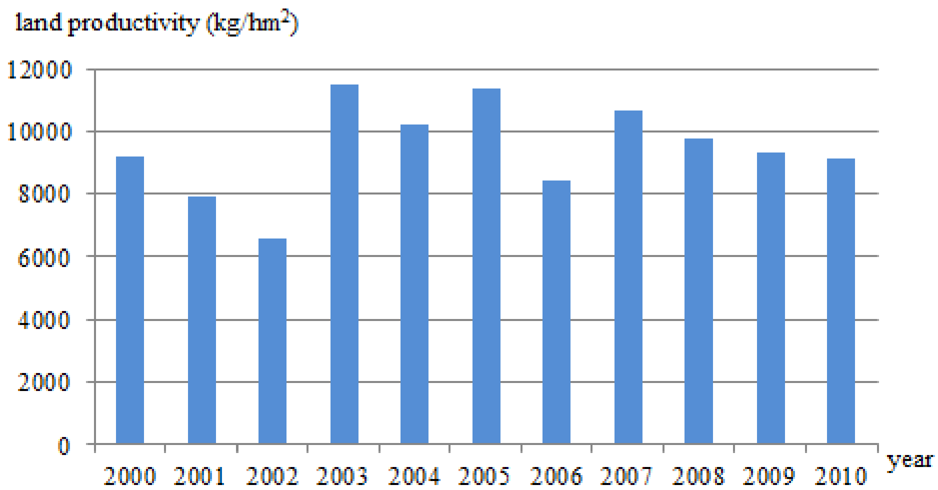


Fig.7. Land productivity in Shandong province during 2000-2010.

4.3 Trade-offs between cultivated land conversions and land productivity

The information from Equation (18) and Figs. 2, 3 and 6 proves the threat of competition between cultivated land and built-up land on the land productivity. It is of great significance to analyze the trade-offs between cultivated land conversions and land productivity to preserving the land productivity. A number of land use related policies are launched trying to slow down the pace of cultivated land conversions, e.g., the balance of total amount of cultivated area, land use regulation system, land use planning, basic farmland protection. However, the average annual area of cultivated land transforms into built-up land during 2000-2005 and 2005-2008 was 27583 hm^2 and 34910 hm^2, respectively, indicating that the loss of cultivated land became more severe. Moreover, the loss of land productivity can't be offset by the quantitative balance since Figs. 2 and 3 showed that land productivity of built-up land was much lower than that of cultivated land. Some measures should be taken to get rid of the negative externalities of cultivated land conversions, and it seems that the most effective path is still to prevent the cultivated land conversion.

Current policies on preventing cultivated land conversion involve land use control system, basic farmland protection and so on. But some of the policies like balance system of farmland requisition and compensation, are criticized by neglecting the trade-offs between cultivated land conversions and land productivity. Then, land productivity is still decreasing while so many related policies and regulations are implemented to prohibit cultivated land conversions. Therefore, the concept of their trade-offs should be planted into the policies and regulations.

5 Discussion and Conclusions

This research analyzes the trade-offs between cultivated land conversions and land productivity in Shandong province during 1985-2010. Our research results show that land productivity is unevenly distributed in Shandong province, which is relatively lower in regions covered by built-up land. Although expansion of built-up land threatens the land productivity, cultivated land conversions still occur, while the conversion pace slows down. Moreover, cultivated land conversion influences land production simultaneously through the change of cultivated land area, change of land productivity and their synergistic effects, and therefore controlling cultivated land conversions is one of the most effective ways to preserve land productivity, which is closely associated with the provisioning services of ecosystems.

Roughly speaking, one of the strength of our research is to estimate land productivity with the ESLP which is capable of the identification of substitutability between each of land use types and crop types as well. The ESLP adopts multi-objective programming to estimate land productivity influenced by various kinds of factors including soil properties, climate factors, solar radiation, land resources and even other management information within some certain social and economic context.

However, our study is still far from perfect enough and further study is still needed. There are uncertainties due to some parameter values, which may reduce the accuracy of the estimated results, while the ESLP is capable of analyzing the changing trends of land productivity under reasonable hypotheses and can provide valuable decision support information for land-use planning and land resource management. Nevertheless, it is still necessary to carry out some further research, for example, this study has not estimated the accurate contribution of cultivated land conversion to change of land productivity. Moreover, land productivity is influenced by both natural factors and human activities, but more natural factors are considered in the estimation of land productivity based on ESLP, and it can be further improved by involving the contribution of cultivated land conversions to land productivity in the future research.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgements

This research was supported by the National Natural Science Foundation of China for Distinguished Young Scholars (Grant No. 71225005); the data was supported by the Key Project in the National Science and Technology Pillar Program of China (Grant No. 2013BACO3B00), and the STS-Network Project of Chinese Academy of Sciences (Grant No. KFJ-EW-STS-058).

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Chapter 7: Does Expressway Consume More Land of the Agricultural Production Base of Shandong Province?

This paper has been published in *Computational Economics*
https://doi.org/10.1007/s10614-017-9747-8.

Abstract

The effect of expressways on cultivated land is ambiguous. Many studies conclude that building and upgrading expressways increases pressure on cultivated land while others find expressways reduce the rate of cultivated land loss. In this paper, we use satellite remote sensing images of cultivated land in Shandong province of China to test whether the existence of expressway in 2005 affected the level of cultivated land in 2010 and the rate of change from 2005 to 2010. To account for expressway access for each of our1 km^2 ('pixel') units of cultivated land we measure whether or not and what type of roads penetrate the 'watershed' in which the pixel lies. These watersheds allow more plausible measures of accessibility than those traditional 'crowfly' distance measures that ignore topography. To account for possible confounding we also use 24 additional covariates. Although simple univariate OLS regressions analysis show that cultivated land is always lower while cultivated land increasing rates are higher either when there is an expressway, these results are not robust. Controlling for all of the covariates and also using recently developed covariate matching techniques to estimate treatment effects, we find that expressway can most safely be described as putting a positive impact on cultivated land changes.

Keywords: Cultivated land; Expressway; Land use; Covariate matching; PSM model; Shandong province.

1 Introduction

Expressways are a fairly recent addition to the transportation infrastructure in China. Previously, the national road network consisted of a system of at-grade China National Highways. It is an integrated system of national and provincial-level expressways in China. Since the middle of 1980s, in order to meet the increasing need of economic growth, expressway has been developed rapidly in China. At the beginning of 21st century, the total mileage of expressway in China has reached nineteen thousand kilometers, which ranked second in the world after the United States. With the opening of National western development strategy, strengthening the highway construction, especially the highway of high grade is an important base for developing the western region. The country's economic growth has been accompanied by the sparkling growth of the nation's transportation infrastructure. According to the database given by National Bureau of Statistics of China (NBSC, 2014), the total highway mileage of China reached an amazing 4.46 million kilometers by 2014.

According to the database given by the World Bank (2014), the cultivated land in China has decreased significantly since 1990, for the reason of ecological restoration, rapid urbanization as well as real estate development. However, as the speed of ecological restoration has slowed down since 2007, the rate of cutting down the quantity of cultivated land has lowered, or even showed an increasing trend in the area of the cultivated land (Liu et al., 2010). With rising concern over food security related to cultivated land loss, increasing efforts are being made by economists, ecologists, geographers and other scientists to understand the direction, rate and intensity of cultivated land change (Chen et al., 2009; Jiang et al., 2013).

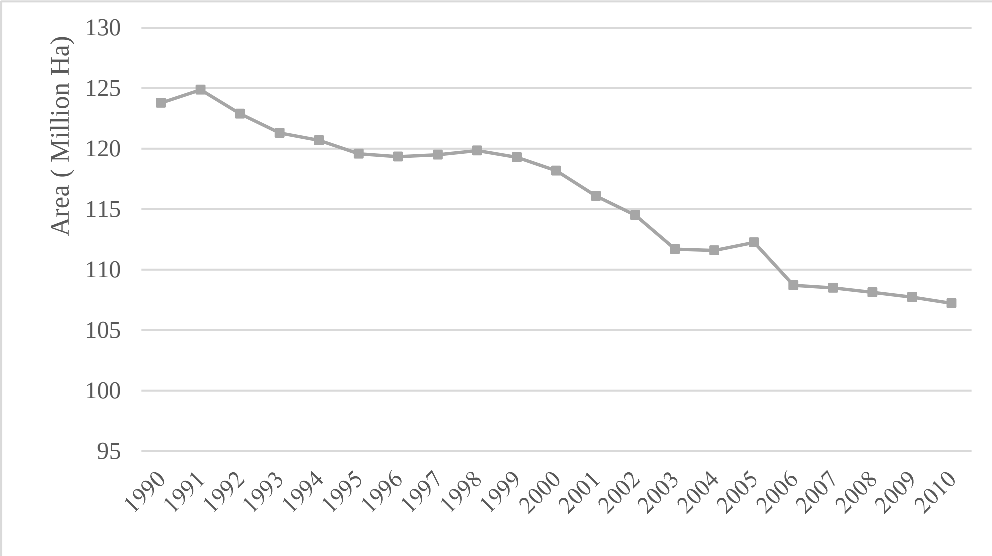

Fig. 1 The area of cultivated land in China from 1990 to 2010

Data source: World Development Indicators from World Bank, 1990 - 2010

Nowadays, both rural development and urban development in China are experiencing a transition period that is the reconstruction of a traditional agricultural society into a modern industrial and urban society. With the accelerated rural industrialization and urbanization process, rapid population growth and development of the market economy, the industrial structure, employment structure and land-use pattern in the coastal region of China have been transformed enormously. Long et al. (2009) pinpointed that rapid industrialization along with urbanization had greatly changed the rural areas in the facet of cultivated land loss for factory workshop, and rural labors transformation for workers. Since the year of 1978, agriculture and the rural area have made a big contribution to the development of industries and the cities in China. As a result, a series of problems along with the social and economic development of China appeared, such as decreasing cultivated land, degrading environment, widening the income gap between urban and rural area, and so on (Gibson and Rozelle, 2003; Xie and Zhou, 2014; Wang et al., 2016).

Currently, the determinants of cultivated land loss have attracted interests among a wide variety of researchers, ranging from those who are modeling the spatial and temporal patterns of land conversion, to those who try to understand the causes and consequences of land-use changes (Irwin and Geoghegan, 2001; Liu et al., 2008; Gennaio et al., 2009; Deng et al., 2015). To some extent, cultivated land loss is still a complex issue regarding its process, dynamic and driving forces (Jiang et al., 2012; Kuang et al., 2016; Tegegne et al., 2016). The literature shows that various geophysical factors, such as slope and elevation, demographic factors, economic variables and policies of governments are all important correlates of cultivated land and its changes. Therefore, a single research approach does not suffice for a complete analysis on impacts of road buildings on cultivated land. Instead, a combination of multiple approaches is necessary (Long, 2009; Song et al., 2012; Laurance et al., 2014).

There are an increasing number of researches which have focused on the relationship between roads and cultivated land. In many instances, roads are found to lead to cultivated land loss. The logic is that when a road enters an area (or when it is widened or improved), pressure will rise and then cultivated land will fall. An important implication of what we characterize as this "pressure cooker" hypothesis is that "road networks may significantly shape the spatial pattern of remaining cultivated land" (Deng et al., 2011). Hence, road investments in cultivated land are thought to lead to cultivated land loss.

According to this "pressure cooker" hypothesis, when new or better roads reach into a region, access to transportation and new and more convenient linkages to the outside world encourages economic growth, produces jobs and increases agricultural productivity (by making inputs cheaper, agricultural technology more accessible and farm-gate prices of agricultural commodities higher). If these dynamics are able to refocus the livelihood strategies of households that previously were encroaching on cultivated land onto intensive (river-bottom; irrigated) agriculture and off-farm employment, including migration, the pressure on the cultivated land might be reduced. In fact, there has been a fairly large literature that discusses the mechanism that may be underlying the pressure-valve hypothesis. Such a phenomenon could arise in part as a result of increased opportunities to purchase inputs that increase or maintain yields (Gibson, 2002, Gibson and Olivia, 2010; Song et al., 2013; Turkseven and Ueda, 2017).

Since existing evidence on the effects of roads on cultivated land is unclear, and has not always benefited from latest refinements in data and methods, new evidence is required. Specifically, we use the remotely sensed digital images by the Landsat TM/ETM satellite with a spatial resolution of $30 \times 30m^2$ covering Shandong province, China, to test whether the existence of roads in 2005 affected the level of cultivated land in 2010 and the rate of change from 2005 to 2010. To account for road access for each of our 1 km^2 (‘pixel’) units of cultivated land we measure whether or not roads in the “city corridor” exists. City corridor is one of spatial forms of city system, and it has a long history in regional and urban development and planning. To account for confounding from the exclusion of other relevant variables and potentially biased estimates of treatment effects due to the endogenous placement of roads, we use covariate matching techniques, using 24 additional covariates. Our overall goal is to discover if roads are delegating more like "pressure cookers"—and are associated with lower levels of cultivated land and greater rates of cultivated land loss in Shandong province—or more like "pressure valves"—and are associated with higher levels of cultivated land and lesser rates of cultivated land loss (or are neutral).

To meet these objectives, the rest of this paper is organized as follows. The next section is an overview of the study area, the third section is about the definitions (explained and explanatory variables) and data used in this study. The dependent variable, the level of cultivated land (in some regressions—and the change in cultivated land in others), is defined and the approach that we use to measure access to expressway is described. The fourth section lays out the econometric approach that we use to explore in greater depth the relationship between expressway and cultivated land loss. Our main strategy in this analysis is to look at the simple relationship between expressway and cultivated land loss, by including covariates to measure the net effect of expressway on cultivated land changes, and use matching methods to at least in part control for observed and unobserved differences between pixels that have different degrees of access to expressway in order to obtain unbiased treatment effects estimates, of what happens to the cultivated land. The final section reports the estimation results, discusses the key findings and concludes as well.

2 Study Area

In this study, we selected Shandong province, a coastal province of China, as our study area. Shandong province is located at the intersection of ancient as well as modern north–south and east–west trading routes have helped to establish it as an economic center. There are totally 17 cities in Shandong province, which includes Jinan, Qingdao, Zibo, Zaozhuang, Dongying, Yantai, Weifang, Jining, Taian, Weihai, Rizhao, Laiwu, Linyi, Dezhou, Binzhou, Liaocheng, Laiwu. Now Shandong province has emerged as one of the most populous (95,793,065 inhabitants at the 2010 Census) and most affluent provinces in the People's Republic of China with a GDP of 5.942 trillion yuan, or 967 billion US dollars in 2014, making it China's third richest province (Fig. 2).

Fig. 2 Geographical location and administrative boundaries of Shandong province

Shandong province ranks first among the provinces in the production of a variety of products, and it is also the largest agricultural exporter in China. Besides, the total length of expressway in Shandong province ranked second among whole China in 2014(NBSC, 2015), so this study on the impacts of expressway on cultivated land in

Shandong province is of great importance to the major livelihood (Fig. 3). The relations between expressway and cultivated land are showed in Fig. 4. We can observe the clear correlation between the two sides changing from 2005 to 2010.

Fig. 3 Distribution of cities and expressway in Shandong province

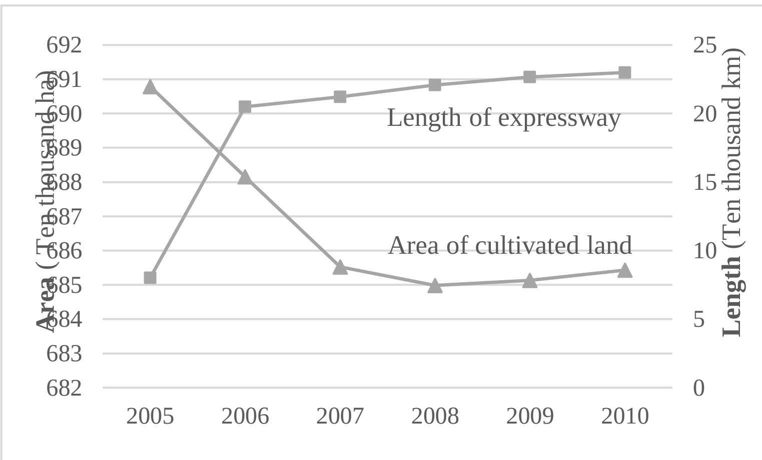

Fig. 4 Temporal changes of length of expressway and area of cultivated land of Shandong province from 2005 to 2010

3 Data and Variables
3.1 Data

One of the strengths of our study is the quality of data that we use to estimate the cultivated land in given years and changes in cultivated land over time. For our purposes, we believe that variables based on satellite remote sensing digital images are the most suitable measures that can be used for detecting and monitoring land use change at global and regional scales (Geist and Lambin, 2001; Kok, 2004; Deng et al., 2006). In China, land use change—including changes in cultivated land—has been tracked by remote sensing data and results of the empirical exercises have been reported in the literature (Shi, 2000; Sato and Yamamoto, 2005).

In our study, we use a land use database developed by the Chinese Academy of Sciences (CAS). The original data are from satellite remote sensing data provided by the US Landsat TM/ETM images which have a spatial resolution of 30 by 30 meters. These have been aggregated by CAS into 1 km by 1 km picture elements ('pixels') and these are the observations used in this study. The database includes time-series data for three time periods: a.) the mid-1990s, including Landsat TM/ETM scenes from 1995 and 1996 (henceforth, 1995); b.) the late 1990s, including Landsat TM/ETM scenes from 1999 and 2000 (henceforth, 2000); c) the late 2000s, including the data from 2005 to 2010 (henceforth, 2010). For each time period, more than 500 TM/ETM scenes were used to cover the entire country. The data team also spent considerable time and effort to validate the interpretation of TM/ETM images and land-cover classifications against extensive field surveys (Liu et al. 2003, Tan et al., 2005). A hierarchical classification system of 25 land-use classes was originally applied to the data and we aggregate these further into six classes of land use–forest land, forestry area, grassland, water area, built-up area and unused land. In this study, we only use information from the data set on cultivated land (primarily as our dependent variable) and built-up area (as covariates). The socio-economic data used in this paper was obtained from Ministry of

Public Security of China (2001), Bureau of Statistics of Shandong (2008), NBSC (2001, 2005, 2007, 2010).

3.2 Variables

3.2.1 Dependent variable— cultivated land and change of cultivated land

The data we used is collected from Shandong province of 2005 and 2010, they can be used to track the changes in the cultivated land. Although decreasing in the aggregate by a small margin, which maps the *differences in the cultivated land* across time for each pixel in the data set, demonstrates two things: Firstly, both cultivated land expansion and cultivated land loss occur at the same time. Secondly, it can be shown that, in fact, the cultivated land in Shandong province is quite dynamic and changing over a large area. One of the main questions that this paper wants to answer is whether expressway would encourage the cultivated land loss directly; or if they are part of the set of forces that facilitates cultivated land loss; or if they are in neutral position.

3.2.2 Explanatory variables: roads and other factors

The basic data for our expressway variable came from provincial, county and local maps which were collected from the Chinese Academy of Sciences (CAS) data center. The information from the hard copies of the maps was digitized by a working group based in the Institute of Geographical Sciences and Natural Resource Research, CAS. Although it would be simple to calculate the straight line (“crowfly”) distance from each pixel to the nearest segment of digitized road, such an approach is likely to provide a misleading measure of road access. Almost there are plenty of land area is mountainous or hilly, so travel from many pixels to the nearest road involves going over mountains, which may be impractical. In such an environment, a more realistic measure of accessibility requires knowledge of the topography.

In addition to the information on cultivated land and expressway, other data were used to create control variables for the other factors that determine cultivated land. When looking at the empirical literature on the determinants of cultivated land, there are four broad categories of variables. Chomitz and Gray (1996) and others include a number of geographic and climatic variables. These same authors along with Cropper et al., (1999) also use several demographic and economic variables. Other authors like Pfaff (1998), Robalino et al., (2007) include measures of distance from the cultivated land plots to different features (such as, distance to the nearest city). There are other factors also being used by different authors (such as whether or not the pixel is in a protected area). In order to make our analysis as consistent as possible with the rest of the literatures, we have collected information on four sets of variables: geographic and climatic factors, demographic and economic factors, measures of distance and other factors.

With our data we are able to create fourteen measures of geographic and climatic factors. The data for measuring *rainfall* (measured in millimeters per year), *temperature* (measured in average degrees centigrade per year) and *cumulative temperature* (measured in accumulated degrees centigrade per year) in 2005 and 2010 are from the CAS data center but were initially collected and organized by the Meteorological Observation Bureau of China from more than 600 national climatic and meteorological data centers. For using in our study, we took the point data from the 29 climate stations in Shandong province and interpolated them into surface data using an approach called the thin plate smoothing spline method (Hartkamp et al., 1999). The *elevation* and *terrain slope* variables, which measure the nature of the terrain of each county, are generated from China's digital elevation model dataset that are part of the basic CAS data base. Landform data including *mountain, hill, mesa and plain* are also from the CAS data center. Information on the properties of soil is also a part of our set of geographic and climatic variables from the CAS data center (*organic matter in the top soil* and *loam*). Originally collected by a special nationwide research and documentation project (the Second Round of Chinese National Soil Survey in 2014) organized by the State Council and run by a consortium of universities, research institutes and soils extension centers, we use the data to specify three variables: the nitrogen content of the soil (*nitrogen*—measured in percentage); *available phosphorous* in the top soil (measured in ppm); and *soil pH value*. By using a conventional Kriging algorithm (Kravchenko and Bullock, 1999), we are able to interpolate the soil information into surface data to get more disaggregated information on the property of the soil over space for each pixel.

Two demographic and economic variables, *population* and the level of gross domestic product per square kilometer (*GDP*), are included in our modeling work. The demographic data for 2005 and 2010 are from the *Population Statistical Yearbook for China*. Information on GDP for each county for 2005 and 2010 are collected from the *Socio-economic Statistical Yearbook for China's Counties*. In order to get pixel-specific measures of the demographic variables, we use an approach which is called the Surface

Modeling of Population Distribution framework to interpolate the data across space (measured as persons/kilometer square) (Deng et al., 2008). The level of GDP (GDP per square kilometer) is also interpolated across space using commonly available GIS algorithms (Doll et al., 2000, 2006; Deng et al., 2008).

We also created four measures of distance (all of which are measured in kilometers). These variables are defined separately for each pixel in our sample. *Distance to the nearest road* is measured as the distance (by the shortest road route) from each pixel to the main roads of Shandong province. *Distance to the nearest urban core* is generated by measuring the distance by shortest road route from each pixel to the nearest county seat or other major urban center. *Distance to the expressways* is generated by measuring the distance to the expressways in Shandong province. *Distance to the port city* is the distance to the nearest port city in Shandong province.

Finally, we further obtained data for four other factors. The variable, bufferarea3, bufferarea5, bufferarea7, bufferarea10, indicates whether a pixel is covered by city corridor or not. (See Appendix Fig. 1 for more details about *other variables*). The idea of including this variable is to hold the impact on the cultivated land. The variable is created by measuring the distance to the city corridor within a 1 by 1 km^2 around the pixel. Descriptive statistics for the control variables are included in Table 1.

4 Econometric model

4.1 Basic model

The basic relationship that we are interested in is:

$$Cultivated\ land_{it} = a_0 + a_1 * Access\ to\ Expressway_{i(t-j)} + e_{it} \quad (1)$$

where *Cultivated land*$_{it}$ is the area of the cultivated land in pixel i in year t; *Access to Expressways*$_{i(t-j)}$ is a measure of the nature of the expressway that ran through the watershed which contains pixel i in year t-j; and a_1 is our coefficient of interest. We use a lagged measure of access to expressway to help reduce some of the potential endogeneity bias, since changes in cultivated land between 2005 and 2010 should have no direct effect on expressway in 2010.

Table 1: Descriptive table of the variables used in this study

Variable	Units	Obs	Mean	Std. Dev.
Dependent variables				
Cultivated land in 2010	ha	82634	43.8	1.68
Change of cultivated land between 2005 and 2010	ha	82634	-0.37	-0.52
Geographic and climatic factors				
Elevation	Meter	82634	105.41	139.16
Terrain slope	Degree	82634	72.9	145.89
Landform: mountain	-	82634	-	-
Landform: hill	-	82634	-	-
Landform: mesa	-	82634	-	-
Landform: plain	-	82634	-	-
Organic matter in the top soil	%	82634	0.79	0.18
Loam	%	82634	11.47	2.09
Nitrogen	%	82634	0.05	0.01
Available phosphorous	PPM	82634	5.37	0.94
Soil pH value	–	82634	6.4	0.68
Temperature	degree centigrade	82634	12.65	0.71
Rainfall	Millimeter	82634	1282	309.5
Cumulative temperature(>0°C)	°C		5831.37	729.9
Demographic and economic factors				
Population	persons per square kilometer	82634	645.6	948.8
GDP	10, 000 yuan per square kilometer (2010)	82634	2480.2	4516.7

Measures of distance				
Distance to the nearest road	Kilometer	82634	4.21	3.86
Distance to the expressways	Kilometer	82634	15.8	14.55
Distance to the near urban core	Kilometer	82634	43.7	21.9
Distance to the port city	Kilometer	82634	219.8	68.9
Other factors				
Bufferarea3, expressway pixel is inside or not	1/0	82634	0	1
Bufferarea5, expressway pixel is inside or not	1/0	82634	0	1
Bufferarea7, expressway pixel is inside or not	1/0	82634	0	1
Bufferarea10, expressway pixel is inside or not	1/0	82634	0	1

Notes: Statistics based on the sampled data set of 1 by 1 km^2 with total number of pixels up to 82634.

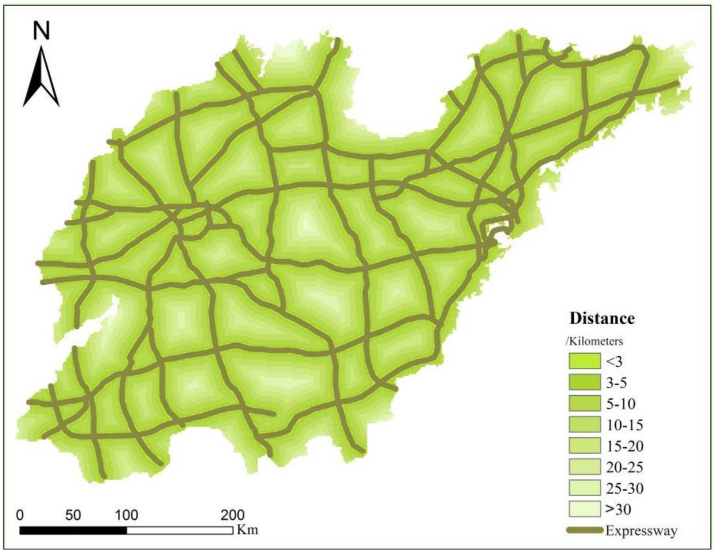

Fig. 5 Distance of each pixel to the nearest expressway in Shandong province, 2010

Since we are interested in the impact of whether there is a road in the watershed (or not) as well as the type of road (expressway vs. province-level highway vs. other road), we define Access to Roads $_{it-j}$ in four different ways. In model 1.1 we will include in our sample only the expressway and province-level highway pixels and Access to Roads $_{1.1it-j}$ will equal 1 if the pixel is an expressway pixel and will equal 0 if the pixel is on a province-level highway. This is called Treatment 1 in the rest of our paper. Note, the other road pixels and no road pixels are excluded from the analysis when we use Access to Roads $_{1.1it-j}$. In the estimation of model 1.1, a $_{1.1}$ will measure the effect on cultivated area of changing a highway system from a province-level highway to an expressway.

In model 1.2, we will include in our sample only the expressway, province-level and other road pixels and Access to Roads $_{1.2it-j}$ will equal 1 if the pixel is either an expressway pixel or a province-level highway pixel and will equal 0 if the pixel is an "other road pixel". In the estimation of model 1.2, a 1.2 will measure the effect on cultivated area of changing a highway system from some other road to either an expressway or province-level highway. This is called Treatment 2. The roadless pixels are dropped from the analysis when we work with model 1.2.

In models 1.3 and 1.4, we use the full sample. The empirical exercise in model 1.3 will be like that of model 1.2, except we set Access to Roads $_{1.3it-j}$ =0 when the pixels are either other road pixels or no road pixels. In this way, the interpretation of a $_{1.3}$ becomes the effect on cultivated area of changing a highway system from some other road to either a province-level highway to an expressway or of building a province-level highway or expressway to a previously roadless watershed (Treatment 3). In model 1.4, we set Access to Road $_{1.4it-j}$ =1 if there is any type of road in the watershed and set it to 0 if there is no road in the watershed. The interpretation of a 1.4 becomes the effect on cultivated area of building any type of road to a previously roadless watershed (Treatment 4). Table 2 summarizes the different treatments that we will conduct by estimating models 1.1–1.4.

Table 2: Definition of treatment and control variables for four alternative treatments

Alternative treatment	Treated—the largest type of road that goes through the watershed is:				Control—the largest type of road that goes through the watershed is:			
	Expressways	Province-level highways	Other roads	No roads	Expressways	Province-level highways	Other roads	No roads
Model 1.1: Expressways vs. province-level highways	X					X		
Model 1.2: Expressway and/or province-level highways vs. other roads	X	X					X	
Model 1.3: Expressway and/or province-level highways vs. other roads or no roads	X	X					X	X
Model 1.4: Expressway and/or province-level highways and/or other roads vs. no roads	X	X	X					X

Equation (1) is problematic for several reasons. Pixels in watersheds with expressways are likely to differ from those in watersheds without any roads (or with only minor roads) in many ways. They may have easier topography and more productive soils along with unobserved locational advantages, since richer areas (or areas with more development potential) are more likely to attract investment in roads. Hence, applying OLS to Equation (1) is likely to give biased and inconsistent estimates. Indeed, as discussed above, previous work suggests many other factors that might affect cultivated area and since some are likely to be correlated with both cultivated area and access to roads, we can reduce omitted variable bias by controlling for as many variables are possible. This gives the model:

$$Cultivated\ land_{it} = a_0 + a_1 * Access\ to\ Expressway_{i\ (t\text{-}j)} + a_2 * Z_i + e_{it} \qquad (2)$$

where in addition to the variables and parameters in equation (1), the specification of Z in equation (2), includes eight measures of geographic and climatic variables (*rainfall, temperature, cumulative temperature, elevation, terrain slope, nitrogen, available phosphorous and soil pH value*); two measures of demographic and economic variables (*population, GDP)*; two measures of distance variables (*distance to the provincial capital, distance to the nearest urban core)*. Since the other variables in Z are only vary across space, we only include an *i* subscript on *Z*.[1]

While adding covariates to an OLS regression (as in equation 2) allows differences in the average values of observed characteristics to be controlled for, many studies show that this is a relatively inflexible and unsuccessful way to deal with the sample selection problem that occurs when observations in non-experimental studies cannot be randomly assigned to "treatment" and "control" groups. On the other hand, matching is an increasingly popular non-experimental evaluation method, with proponents claiming that it can replicate experimental benchmarks when appropriately used (Dehejia and Wahba, 2002). In particular, matching offers a way of structuring non-experimental data to look like experimental data, where for every subject in the "treated" group, the researcher finds comparable subjects in the "control" group.

In other words, while adding *Z* may help controlling for some of the factors that might create an omitted variables bias problem when estimating a_1, using Ordinary

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[1] To avoid over-controlling, we do not include in the Z_i matrix of equation. The variable, *distance to nearest road*, measures the distance from each grid cell to the nearest road of any type. We generated the variable, *road density* within the watershed by measuring "the length of all roads per square kilometer (m/km^2).

Least Squares (OLS) assumes that simply conditioning linearly on Z variables suffices to eliminate selection bias. While the linear model can approximate a given non-linear function of the Z arbitrarily well when sufficient higher order terms are included, most of the linear regression models in the literature do not include higher order terms. Hence, for such models, using the standard OLS estimation approach would also be biased.

4.2 Matching methodology

The matching method is another way to examine the impact of a treatment (in our context, existence of expressway) on an outcome (in our case, cultivated land) when selection takes place on observable characteristics. Also, just as in a standard OLS model, measuring the effect of expressway on cultivated land without bias using the matching method assumes that the outcome in the base state is independent of the treatment, conditional on observed covariates Z. In other words, for pixels within subgroups defined by Z, being located in a city corridor with expressway is unrelated to what the cultivated land would be if the pixel were not in a city corridor with roads. This is the so-called Conditional Independence Assumption. If this assumption holds, we can say that given the observable covariates, the cultivated land of the control pixels are what the cultivated land of the treated pixels would have been had they not had the expressway.

Unlike OLS, however, matching works by finding a control pixel that is very similar to the treatment pixel by conditioning on Z variables non- parametrically rather than linearly (Black and Smith 2004). Moreover, with matching methods, but not OLS, we can impose “common support,” which excludes treated pixels for which we cannot find reliably similar control pixels.

To take advantage of these factors, we follow the recent literature and match every treated pixel with a control pixel using covariate Matching and its variants. With covariate matching (Abadie and Imbens, 2006), we estimate the average treatment effect by comparing outcomes between treated observations—pixels in a watershed with a specific type of road—and control observations—pixels in a watershed without the specific type of road.

Covariate matching, the method created by Abadie and Imbens (2006), matches directly on covariates. In our analysis, we choose to match the two nearest neighbors with the similar covariates (Z), where the variables in Z are the same as in the OLS model. Within these pixels, we can then directly estimate $E(Y_{i1}|T_i=1, Z_i)$ and $E(Y_{i0}|T_i=1, Z_i)$. This approach means that once we have a matched sample, we compare the cultivated land of the treated pixel with the cultivated land of the controlled pixel. We also report the estimated coefficients that use the post-matching bias correction factor also developed by Abadie and Imbens (2006). This correction factor is needed to correct for the conditional bias in finite samples when there are three or more continuous variables. The recent work demonstrates that bootstrapping standard errors are invalid with non-smooth nearest neighbor estimators.

4.3 Spatial sampling

The basic unit of observation in our study is the 1 km^2 pixel, of which there are 82634 in Shandong province. There is a high correlation in cultivated land between neighboring pixels and a lesser but still statistically significant correlation in the residuals of the OLS estimates of equation (2).[2] At the very least, this spatial autocorrelation can lead to inefficiency and invalid hypothesis testing procedures but it may also cause biased and inconsistent parameter estimates if spatial interactions are present such that a spatially lagged dependent variable belongs in the model (Anselin, 1995).

We take three approaches to dealing with this spatial autocorrelation problem. First, rather than using all pixels we take a 1-in-25 sample by choosing only the pixels at the vertices of a 5 km by 5 km grid. Second, since we use matching methods this eliminates even more of the spatial autocorrelation because every treated pixel is matched with a control pixel. Except for the extreme case where the two matched pixels share a common watershed boundary, the pixels are unlikely to be adjacent neighbors.

4.4 Summary of our estimation approach

Given the proceeding discussion, in order to estimate the effect on cultivated land of access to expressway, we take the following approach. First, we estimate equations (1) and (2) using OLS. Next, we use a covariate matching approach, using two algorithms— "covariate matching using an inverse variance weighting scheme" and "covariate matching using a Mahalanob is weighting scheme." We use these estimators to analyze the effect of expressway in the city corridor on the cultivated land and do so holding constant (in the case of our OLS estimators) and matching on (in the case of our covariate matching estimators) a set of covariates that are described above.

[2] The Moran *I* statistic is 0.73 for the dependent variable and 0.49 for the residuals. Intuitively, this statistic is equivalent to the slope coefficient of a linear regression of the weighted average value of cultivated cover (residuals) for the pixels surrounding the *i*th pixel on the cultivated cover (residual) in pixel *i*.

In order to check the robustness of our results, we first report the models excluding four variables that may be correlated with our treatment variable and then add them one by one for robustness checks with one of the *Access to Expressway* variables. Furthermore, we estimate all of our equations using both level of cultivated land in 2005 and 2010 ($Cultivated\ land_{i2005}$, $Cultivated\ land_{i2010}$) and the changes in cultivated land ($Cultivated\ land_{i2010} - Cultivated\ land_{i2005} = \Delta\ Cultivated\ land_{i2005}$) using pixels as the units of observation.

5 Results

The simple linear regression using OLS (with no controls and when we divide Shandong province into 9461 watersheds) produces results that are similar to those found in the descriptive analysis above (Table 3, row 1& Table 4, row 1). Regardless of the definition of the roads variable (Treatments 1–4), the larger the road in the early 21st century (or if there is any road vs. no road), the lower the cultivated area in 2010. The signs on the coefficient of the roads variable are negative in all columns, and there are four columns are significant at 1% level, one is significant at 5% level, and two are significant at 10% level, while the remaining one is insignificant. In other words, when we use any treatment variable and when using observations at either the pixel or watershed level, there is a negative and significant relationship between roads in one period (2005) and cultivated lands in the next period (2010). Examining the magnitude of the coefficients demonstrates that the presence (or size) of a road, when we do not control for other factors, is associated with land that has 0.23 -4.41% less cultivated area.

Table 3: Results from Ordinary Least Squares regression approach and covariate matching analyzing the effect of roads on cultivated land in Shandong province at pixel level

Dependent variable: cultivated land area of 2010				
	Expressways vs. province-level highways (Treatment1)	Expressway and/or province-level highways vs. other roads (Treatment2)	Expressway and/or province-level highways vs. other roads or no roads (Treatment3)	Expressway and/or province-level highways and/or other roads vs. no roads (Treatment 4)
OLS, no control	-0.289 (-1.23)	-0.932 (-1.89) *	-0.234 (-4.56) ***	-1.377 (-8.62) ***
OLS, with covariates	-0.193 (-1.49) *	-0.252 (-1.57) *	-0.102 (-1.79) *	-0.152 (-2.56) **
Covariate matching (inverse variance)	0.181 (0.66)	0.172 (0.82)	1.068 (1.72) *	1.142 (2.76) **
Covariate matching (Mahalanobis)	1.806 (1.53) *	1.127 (1.82) *	1.279 (2.78) **	0.232 (2.41) **
N treated	1250	2908	2908	5076
N available controls	1191	995	1606	1590

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 4: Results from Ordinary Least Squares regression approach and covariate matching analyzing the effect of roads on cultivated land in Shandong province at watershed level

Dependent variable: cultivated land area of 2010				
	Expressways vs. province-level highways (Treatment1)	Expressway and/or province-level highways vs. other roads (Treatment2)	Expressway and/or province-level highways vs. other roads or no roads (Treatment3)	Expressway and/or province-level highways and/or other roads vs. no roads (Treatment 4)
OLS, no control	-1.879 (-1.91) *	-1.214 (-2.74) **	-4.412 (-4.78) ***	-4.321 (-5.20) ***
OLS, with covariates	-0.696 (-0.71)	-1.621 (-1.86) *	-1.128 (-1.98) *	-0.217 (-1.71) *
Covariate matching (inverse variance)	1.313 (0.80)	1.014 (1.99) *	2.752 (2.53) **	0.223 (1.42) *
Covariate matching (Mahalanobis)	1.496 (1.06)	1.762 (1.11)	1.526 (1.89) *	1.231 (1.27) *
N treated	153	328	328	559
N available controls	131	120	479	265

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Importantly, as soon as we add the 24 covariates defined above to the OLS model, the negative association between roads from 2005 to 2010 and the level of the cultivated area in 2010 still remains (Table 3, row 2 & Table 4). Regardless of the treatment or the level of observation (watershed or pixel), point estimates of the relationship between roads and cultivated area are negative in all eight models, with most of figures are statistically significant. Therefore, the most accurate interpretation of the findings when we estimate Equation (2) is that roads have significant negative impact when it comes to influencing cultivated area in Shandong province.

The absence of an impact of roads on cultivated land in Shandong province in 2010 is reinforced when we use the two covariate matching approaches to estimate treatment effects (Table 3 & Table 4, rows 3 and 4). Regardless of the treatment variable and whether we use pixels or watersheds as our units of observation, there is no case where we find a negative and significant impact of roads on cultivated area. In fact, in all 16 different models the signs on the road variables are positive. Hence, we can most accurately classify the result as having nearly no effect. In other words, in our analysis there is no evidence to suggest that roads are creating pressures on cultivated area. In this way, we can find a positive relationship between roads and cultivated area.

The positive relationship between roads and cultivated area is in a strict statistical sense also supported by the simple linear regression of the change in cultivated area on roads (Table 5, row 1). In all of the four models (considering different treatments), the signs on the road variable of treatments 1 and 2 are negative, while of treatments 3 and 4 are positive. Especially in Treatment 4, the coefficients are positive and significantly different than zero.

After controlling for covariates and after implementing our two matching schemes (Table 4, rows 2–4), our interpretation of the findings uses the change of cultivated area as the dependent variable continues to be consistent with the findings when using the level of cultivated area as the dependent variable. At watershed 50 level, there are three of the four signs are negative, while most signs at watershed 100 level are positive. However, in those cases, whether the sign of the coefficient is positive or negative, statistically there is no discernible relationship between roads and change of cultivated area.

Finally, before concluding that the findings from Shandong province, we want to make sure that the results hold up to more conventional analysis. To show this, instead of using our variable of interest (whether or not and what type of roads penetrate the watershed or pixel), we want to examine the coefficients on more traditional measures of road access (e.g., measures based on straight line distance to a pixel or watershed, etc.) and using more standard regression approaches (i.e., OLS instead of matching methods). In this sensitivity exercise, we use two types of data sets (pixels, watersheds) and three different measures of roads (watersheds crossed by roads; distance to roads and road density). The results of the sensitivity analysis (not shown for brevity) using the more traditional measures of roads also show that there is no impact of roads on change in cultivated land in Shandong province. Therefore, the substance of the results using our new approach is also found using more traditional methodological approaches.

Table 5: Estimated model of the impact of road on cultivated land from 2010 to 2005

Dependent variable: cultivated land area, 2010 to 2005				
	Difference-in-Difference			
	Expressways vs. province-level highways (Treatment1)	Expressway and/or province-level highways vs. other roads (Treatment2)	Expressway and/or province-level highways vs. other roads or no roads (Treatment3)	Expressway and/or province-level highways and/or other roads vs. no roads (Treatment 4)
At pixel level	-0.41 (-0.354)	-1.29 (-0.967)	1.35 (0.352)	4.86 (0.932) ***
At watershed50 level	0.16(0.383)	-1.15 (-3.472)	-0.65 (-1.606)	-0.32 (-0.847)
At watershed100 level	0.59 (2.141)	-6.12 (-15.120)***	0.24 (0.866)	0.40 (1.672)

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

6 Conclusions and discussion

In this paper, we have sought to estimate the impact of expressway on cultivated land and the change in cultivated land in Shandong province. Using satellite remote sensing data to track changes over time at the 1 km^2 pixel level, we have found that Shandong province experienced a fall in cultivated land during 2005-2010. Then, we analyzed the determinants of these changes, focusing mostly on the role of expressway in the city corridor.

To estimate the impact of the presence (or the size) of expressway on cultivated land in the city corridor, we developed an empirical framework in which we assigned pixels—the level of observations on which we can observe cultivated land— labels indicating whether or not the 1 km by 1 km land area is easily accessible by expressway. Holding constant a set of carefully defined geographic and climatic factors; demographic and economic variables, distance variables and other factors, we sought to measure the net impact of the nature of the expressway in the mid-1990s on the level of the cultivated land in 2005 and 2010 and the change of the cultivated land between 2005 and 2010. Using both standard OLS with covariates and two covariate matching methods, we found that expressway in the city corridor had no contribution to cultivated land. In other words, according to the findings from three different empirical approaches, when expressways were in larger corridor, they did not appear to be exerting any pressure onto the cultivated land.

However, when an area is long settled or comparatively isolated, and when population densities are fairly high, it is possible that when roads enter an area, they can act as an approach to reduce the cost of moving out of the region or depressing the cost of technologies that will encourage more intensive cultivation/use of land resources in non-cultivated areas. If this were the cases, roads could lead to increasing utilization efficiency of cultivated land, which can be considered as the positive effect on the expansion of cultivated area.

Clearly if these two interpretations are true, it is possible that our research findings are accurately portraying the situation in Shandong province. Shandong province has been settled for thousands of years. The population pressures in many regions of the province become quite high, especially after entering the 21st century. As the frequency of communication with the outside based on the convenient roads, an increasing number of youngsters have migrated to other regions, which may lead to the consequences of lower pressure on cultivate land. Hence, our results may be reasonable. However, we still don’t know whether the quality of the cultivated is rising or deteriorating under the influence of roads. Future research might include the impact on value of the cultivated and other ecosystem services provided by cultivated area.

Then some limits need to be addressed in our study. First, we recognize that we have grouped different types of cultivated area into a single measure. As a result, we are unable to measure the transition between different types of cultivated area (e.g., from high to low quality). If roads affect this transition, but do not lead to de-cultivation, we will ignore these impacts.

In addition, we are also able to measure only the impact of roads on the cultivated area in 2005 in Shandong province. We do not have data on which of the roads are newly built and which have been around for a period of time. Consequently, the available data do not allow us to identify the impacts of roads separately from the impacts of all of the history of human settlement and activity, which is likely correlated with where the roads have been placed over time. Both this historical human activity and roads may shape the current spatial pattern of the cultivated area, making it difficult to identify the impact of roads. However, there is few reason to support us to believe that this omitted history will affect the recent change in cultivated cover, so the similarity of our results showing neutral impacts of roads on the change of cultivated area reduces concern about possible biases in our estimated impact of roads. Future research could consider searching for instrumental variables that show why roads have developed over time in some parts of Shandong province but not others.

However, due to the limitation of the data, we only focused on the relationship between uprating expressways and cultivated land in Shandong province in 2005 and 2010. However, the figure in two years is less representative, that is to say, we cannot know the whole process of land use changing and the conflicts with infrastructure without observation and evaluation over years. In addition, for the contemporary of data, latest data should be used in the future studies.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgements

This research was supported by the National Natural Science Foundation of China for Distinguished Young Scholars (Grant No. 71225005); the Key Project of National Natural Science Foundation (Grant No. 71533004) and the National Natural Science Foundation of International/Regional Cooperation and Exchange Programs (Grant No. 71561137002).

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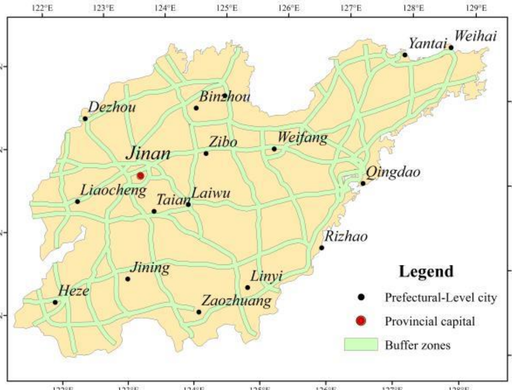
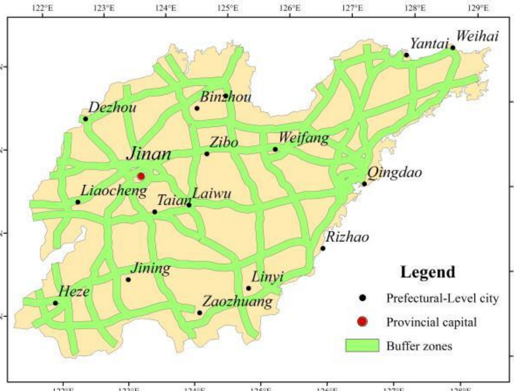
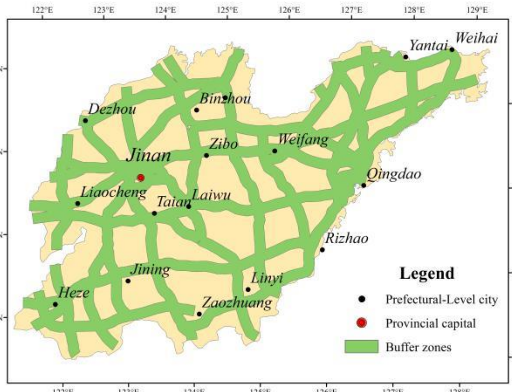
Appendix Fig. 1 Distribution of cities overlaid with a road network buffered with a radius of 3km(a), 5km(b), 7km(c) and 10km(d)



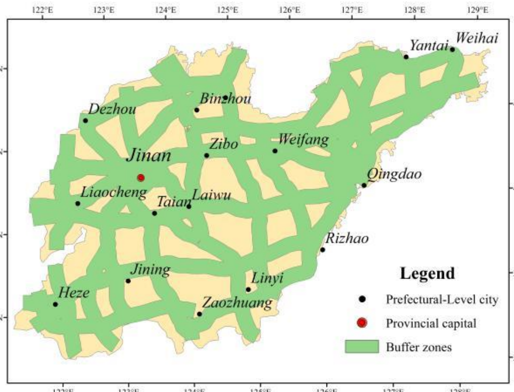
(a)



(b)



(c)



(d)

Chapter 8: Improving Eco-efficiency for the Sustainable Agricultural Production: A Case Study in Shandong, China

This paper has been published in *Technological Forecasting and Social Change* https://doi.org/10.1016/j.techfore.2018.01.027.

Abstract

With rapid economic growth and urbanization in China affecting agricultural land, it is of great importance to improve eco-efficiency for sustainable agricultural development to ensure food security. Shandong, as a key agricultural production base in China that experiences accelerated urbanization, was chosen as our case study area. Supported by a large scale natural and socioeconomic data, we estimated land productivity in Shandong, China during 1990-2010 using the Estimation System of Land Production, then analyzed the eco-efficiency based on Stochastic Frontier Analysis. The results showed that land productivity was unevenly distributed in Shandong, with relatively lower values in regions covered by built-up area. The regional eco-efficiency in Shandong was mostly over 0.9, expect for cities located far from the political or economic centers. The results indicated there exists trade-offs between agricultural production and urbanization, and it is necessary to adjust its agricultural technological measures according to local specific conditions to improve eco-efficiency for sustainable agricultural development in Shandong.

Keywords: Land productivity; Eco-efficiency; Cultivated land; Estimation System for Land Productivity (ESLP); Stochastic Frontier Analysis (SFA); Shandong

1 Introduction

China is the most populous nation in the world, and it currently feeds approximately 22% of world population with only 7% of the world's cultivated land. Globally, rising population is expected to lead to a 70% increase in demand for agricultural production by 2050 with current cultivated land not increasing over current levels (FAO, 2015; Tirlapur and Mundinamani, 2015; Guilpart et al., 2017). It is notable that China's cultivated land area per capita is one of the lowest worldwide (Deng et al., 2010). For example, the second national land survey showed cultivated land area per capita in China was 913 m^2, which was less than half of the world average level (Song and Deng, 2015). The total area of cultivated land in China showed a decreasing trend from 1990 to 2010 (Fig. 1).

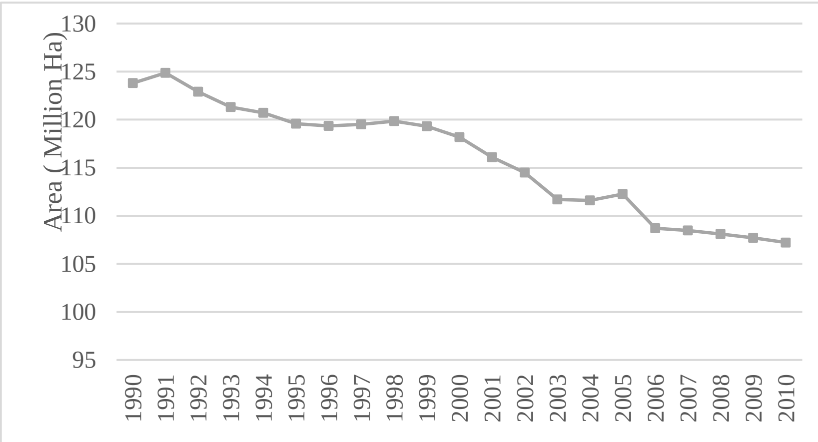


Fig. 1 The area of cultivated land in China,1990-2010
Data source: World Development Indicators from the World Bank.

Based on this background, tracking changes in cultivated land area and impacts on agricultural productivity in China is a prerequisite for the better safeguarding of national food security. However, rapid urbanization in China, along with the implementation of various land policies and ecological protection campaigns, has resulted in changes in the quantity and quality of cultivated land (Wu et al., 2011; Gingrich et al., 2015).

Along with detailed research on land use change, there is growing awareness that eco-efficiency is one of the fundamental factors for ecosystem services improvement and sustainable agricultural production (Deng et al., 2016). The concept of eco-efficiency was introduced as 'a business link to sustainable development' by Schaltegger and Sturm (1990). Regional eco-efficiency is the efficiency with which ecological resources within an area are used to meet human needs (Mickwitz et al., 2006), expressing how efficient the economic activity is with regard to nature's goods and services (Zhang et al., 2008). Eco-efficiency can be improved by reducing environmental impacts and natural resources use while maintaining or increasing the value of the output produced (Mickwitz et al., 2006). Scientific estimation and analysis of eco-efficiency is needed to analyze the impacts of socio-economic development on ecosystem services, with the aim of providing support for land use policy making.

In China, problems regarding land use change and sustainable development of agricultural production are particularly acute in Shandong, which is the third largest agricultural production bases in China (Fig. 2), and so what happens in Shandong affects food security and social stability in all China. Shandong features interactions between crop production, conservation of forestry and grassland covers, and urbanization. The Ministry of Land and Resources of China shows cultivated land per capita in Shandong was just 232 m^2, which is one-quarter of the average for China in 2015. Shandong's importance as an agricultural production base and the loss of cultivated land to development justifies our choice of the region as a study area.

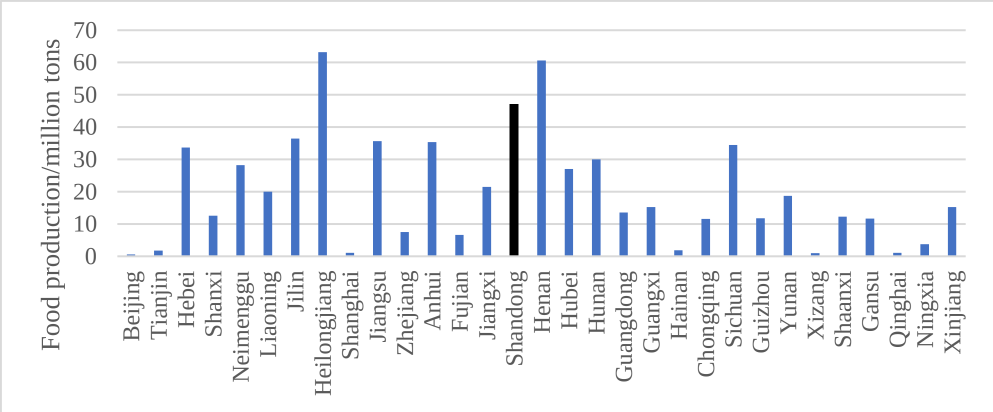


Fig. 2 Food production in all provinces and cities of China, 2015

Data source: NBSC, 2015.

In this paper, we first evaluated land productivity in Shandong based on the Estimation System of Land Production (ESLP). Within the ESLP, agricultural productivity is an indicator of the production capacity of each unit area land, taking into consideration of many socio-economic factors based on land potential productivity (Deng et.al, 2013; Jin et.al, 2015). During the estimation of land productivity, a significant part is the support of large-scale data for the inputs in the ESLP. These can be divided into two main aspects, one is the fundamental inputs to improve land conditions; the other is the conventional production inputs in the specific production process. In addition, we aimed to expand previous studies on the measurement approach and empirical research of regional eco-efficiency. Prior research on eco-efficiency used Data Envelopment Analysis, which only measures inefficiency from a single perspective of input/output, while it is not comprehensive (Li and Hu, 2012). Instead, we evaluated the regional eco-efficiency in Shandong by means of a Stochastic Frontier Analysis (SFA), which will provide scientific support for decision making concerning the sustainability of regional agricultural production.

2 Study Area

Shandong is located on the eastern edge of the North China Plain and the lower reaches of the Yellow River (114°19'-122° 43'E, 34°22'-38°15'N) and borders the Yellow Sea (Fig. 3). There are 17 cities in Shandong, covering a total area of over 151,100 km^2, with plains, mountainous areas and hilly areas accounting for 55%, 15.5% and 13.2% respectively. Shandong lies in the warm-temperate zone with a continental monsoon climate. The annual mean temperature ranges from 11 to 14 ºC and annual precipitation ranges from 550 to 950 mm.

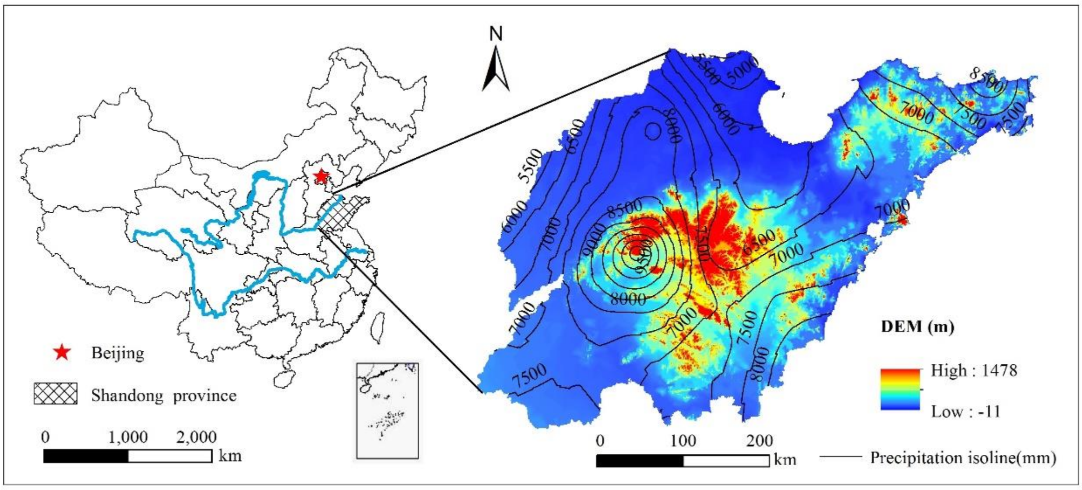


Fig. 3 Geographical location of Shandong Province

Shandong is China's second most populous province with a population of 98.47 million and third richest province with a GDP of over one trillion US dollars in 2015. Shandong ranks first among the provinces in agricultural production, and it is also the largest agricultural exporter in China. However, along with the changes in industrial structure, Shandong experienced obvious land use/cover change and rapid urbanization. The built-up area increased from 34,123 km^2 to 39,110 km^2 during 1990-

2010, while the cultivated land area decreased from 83,623 km^2 to 80,135 km^2 (Fig. 4). Thus, it is important to study the sustainability of regional agricultural production, the results of which may illustrate features of the competing demands for land use in rapidly developing areas (Wang and Zhang, 2010). Urbanization in Shandong has a negative influence on the agricultural development (Song and Deng, 2017). Although grain production in Shandong had been continuously increasing since 2003, the growth rate was decreasing, which maybe primarily caused by land degradation and cultivated land loss (Smith and Gregory, 2013).

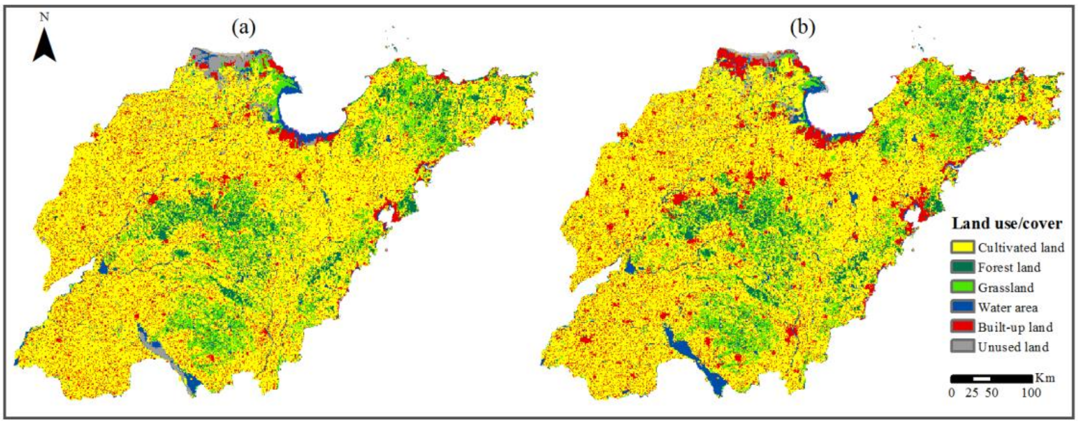


Fig. 4. Land use/cover map of Shandong of the year 1990(a) and the year 2010(b)
Data source: The Data Center, Chinese Academy of Sciences

3 Methods

3.1 Estimation System of Land Production (ESLP)

Land productivity was assessed with the ESLP based on agricultural-ecological zones, which integrated large scale multi-source data, including land use data, climatic data, radiation parameters, and soil properties. In addition, we selected different crop types to calculate land productivity for 25 types of land-use, among which paddy land was primarily used for rice and dry land was mainly used for corn, bean, sorghum and millet.

The average productivity of these five crop types was taken as the light-temperature productivity of cultivated land (Jiang et al., 2011; Hou et al., 2012).

The ESLP consists of two modules, the accumulation module of land resources and the optimization module of land suitability. The first module is decided by the diversity of regional land-use type and land quality, and the second module takes the influencing climatic factors during crop growth in agricultural production into account, with the combination of radiation, temperature and precipitation, to achieve the optimization of coefficients of substitution elasticity and crop types, and further realize agricultural production simulation. The ESLP also provides an open extensible system to apply ecological and economic planning approaches to the development of sustainable agricultural production. We considered not only the natural and social factors that affect land productivity, but also the limiting factors in management. This connects agricultural potential and production inputs to measure the interaction of crops. From the input perspective, these can be divided into two major sections, one is improving the fundamental inputs of cultivated land, the other is the inputs into the specific production type, such as seeds, fertilizers, pesticides, machinery and so on.

The ESLP is conducted based on agro-ecological zones through considering common characteristics that affect crop growth, including the climate conditions, soil properties and other geographic features. Each pixel in an agro-ecological zone should be relatively consistent in the aspect of the growth environment and condition. Then land productivity of each grid was calculated by overlaying information, such as land ownership, land suitability and population carrying capacity. The estimation of land productivity was divided into five steps, namely photosynthetic productivity, light-temperature productivity, climatic productivity, soil productivity and land productivity (Deng et al., 2013).

Photosynthetic productivity is expressed as follows.

$$Y_p = Cf(Q) = K\Omega\varepsilon\varphi(1-\alpha)(1-\beta)(1-\rho)(1-\gamma)(1-\omega) \\ (1-d)sf(1-\eta)^{-1}(1-\delta)^{-1}q^{-1}\sum Q_j \tag{1}$$

where Y_p (kg/hm^2) represents photosynthetic productivity, which refers to the productivity totally determined by photosynthetically active radiation (PAR) with temperature, moisture, soil, crop varieties and other agricultural technical conditions in optimum. C is the unit conversion , K is the area coefficient, Ω is the light use efficiency of crops, ε is the ratio of PAR, calculated as PAR divided by the total radiation, φ is the conversion efficiency of photons, α is the reflectivity of the plant population, β is the transmissivity of flourishing plant population, ρ is the ratio of radiation captured by the organs of crops not for photosynthesis, γ is the ratio of light over saturation point, ω is the proportion of respiration consumption to photosynthate, d is the abscission rate of cauline leaf of crops. s is the economic coefficient of crops, which varies with crop types, natural condition and cultivation techniques, $f(L)$ is the modified value of the dynamics of leaf area of crops, η is moisture content of mature crops, δ is the ash rate, q (MJ/kg) is the heat per dry matter, $\sum Q_j$ (MJ·m^{-2}) is the total solar radiation in the crop growth period.

Light- temperature productivity is presented as equation (2).

$$Y_{lt} = f(T)Y_p \tag{2}$$

where Y_{lt} (kg/hm^2) is the Light- temperature productivity, which refers to agricultural productivity determined by photosynthesis and temperature conditions when moisture, soil, crop varieties and other agricultural technical conditions are at the optimum condition; $f(T)$ refers to the modified function for temperature, which can be written as follows.

$$f(T) = \frac{(T - T_1)(T_2 - T)^B}{(T_0 - T_1)(T_2 - T_0)^B} \tag{3}$$

$$B = \frac{T_2 - T_0}{T_0 - T_1} \tag{4}$$

where T (ºC) represents the average temperature in a certain period, T_0, T_1, and T_2 (ºC) separately refers to the optimum temperature, lowest temperature, and highest temperature during crop growth. $f(T)$ is the asymmetric parabolic function identified by T, T_0, T_1, and T_2, ranging from zero to one. The crop growth period is divided into five stages, namely seeding stage, vegetative stage, reproductive stage, filling stage and mature stage, and $f(T)$ of each stage is calculated.

Climatic productivity can be calculated based on the former two steps, taking precipitation and irrigation into account.

$$Y_w = Y_{lt} f(W)(1 - I) + Y_{lt} I \tag{5}$$

where Y_w is the climatic productivity (kg/hm^2), I is irrigation efficiency, which calculated by irrigated cultivated area divided by total cultivated area, $f(W)$ is the modified coefficient for precipitation, which can be rewritten as follows.

$$f(W) = 1 - K(1 - Pe / ET_m) \tag{6}$$

where K is the production response coefficient, and Pe is the effective precipitation (mm). This can be calculated by the model designed by United States Department of Agriculture (USDA) Soil Conservation Service as follows.

$$\begin{cases} Pe = \dfrac{R(125-0.2R)}{125} & R < 250 \\ Pe = 125 + 0.1R & R > 250 \end{cases} \tag{7}$$

where R (mm) means total precipitation. ET_m (mm) is the largest evapotranspiration in the crop growth period, which can be calculated with equation (8).

$$ET_m = K_1 ET_0 \tag{8}$$

where K_1 is the crop coefficient, related to season, crop type and crop community structure, ET_0 (mm) represents the evapotranspiration rate from a reference surface, which is estimated by the improved Penman-Monteith model, and can be rewritten as follows.

$$ET_0 = \frac{0.408\Delta(R_n - G) + \Phi \dfrac{900}{T' + 273} \mu_2 (e_s - e_\alpha)}{\Delta + \Phi(1 + 0.34\mu_2)} \tag{9}$$

where Δ (kPa·P^{-1}) is the slope of the saturation vapor pressure-temperature curve, R_n (MJ·m^{-2}·h^{-1}) is the net radiation of crop canopy surface, G (MJ·m^{-2}·h^{-1}) is the soil heat flux, which is the energy used for heating soil, $\emptyset$ (kPa·P^{-1}) is the psychrometric constant, T' (ºC) is the mean daily air temperature, u_2 (ms^{-1}) is the wind speed at 2 meters height, e_s (kPa) is the saturation vapor pressure, e_a (kPa) is the actual vapor pressure, and $e_s - e_a$ is the vapor pressure deficit of the air. The soil heat flux can be calculated by equation (10).

$$G = 0.1 * R_n \tag{10}$$

Then soil productivity can be obtained by modifying the climatic productivity (Y_w) with the coefficient of soil availability ($f(S)$).

$$Y_s = f(S)Y_W \tag{11}$$

$$f(S) = \sum_i A_i W_i \tag{12}$$

where A_i represents the factors affecting soil availability, *i* is the number of factors, W_i is the weight of each factor.

Finally, we can calculate land productivity based on the ESLP, which introduces multiple objective analytics to work out the land productivity of each grid using the equation (13).

$$Y = f(I_0, Y_s) \tag{13}$$

where I_0 is the total production investment, and land productivity meets the condition of revenue maximization.

$$f(I, Y_s)P_\theta - I < f(I_0, Y_s)P_\theta - I_0, \nu I \neq I_0 \tag{14}$$

$$\begin{cases} f'(I_0, Y_s)P_\theta = 0 \\ f''(I_0, Y_s) < 0 \end{cases} \tag{15}$$

where P_θ is the expected price of total production investments, f' and f'' are the first and second difference of the function model.

3.2 Eco-efficiency analysis based on Stochastic Frontier Analysis (SFA)

The Stochastic Frontier Analysis (SFA) is applied to calculate the ecological performance indicator (EPI) and eco-efficiency (EE) (Du et al., 2016). The stochastic production frontier model was simultaneously introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and van Denk Broeck (1977). Eco-efficiency and environmental efficiency are developed to express how the performance of ecological factors and environmental factors meet human demand (OECD, 1998; Huppes and Ishikawa, 2005; Huang et al., 2014). Concerns about environmental problems caused by local economic development in developing countries have received much attention in recent years, and the stochastic frontier production function can be used to calculate these two indicators.

To estimate technical efficiency and eco-efficiency, we established a multi-input and multi-output production function, incorporating the ecological variable as one input, and typical land as another necessary input in agricultural crop farming. We assumed that for each period t=1,…,T, the input vectors $X^t \in R_+^N$ could generate output vectors $Y^t \in R_+^N$,

$$S^t = \left\{ (X^t, Y^t) : X^t \, can \quad produce \quad Y^t \right\} \tag{19}$$

According to the goal of the research, we followed the distance function methodology (Song et al., 2012). The input distance function was defined at as follows

$$D_I^t(X^t, Y^t) = \sup\left\{ \lambda : (X^t / \lambda, Y^t) \in S^t \right\} \tag{20}$$

This function treats the output vector Y^t as given and adjusts the input vector X^t if the input-output vectors are still technologically feasible (Song et al., 2014). It should be noted that $D_I^t(X^t, Y^t) \le 1$ if and only if $(X^t, Y^t) \in S^t$. In addition, $D_I^t(X^t, Y^t) = 1$ if and only if (X^t, Y^t) is on the boundary or frontier of technology. So, for the sample *i* of the observations, the expression (21) can be obtained considering the definition of SFA.

$$D_I^t(X_i^t, Y_i^t, t; \alpha, \beta, \gamma, \varphi, \delta, \phi) \exp(v_i - u_i) = 1 \tag{21}$$

where $\alpha, \beta, \gamma, \varphi, \delta, \phi$ are all parameters to be estimated. Here, we will get the stochastic frontier model by adding a term v_i to capture noise, and u_i is defined as the technical inefficiency, where *i.i.d* $v_i^t \sim N(0, \sigma_u^2)$ and $u_i^t \sim N^+(u_i, \sigma_u^2)$. The technical inefficiency model is

$$u_i = \tau_0 + Z_{ij} * \tau_j \tag{22}$$

where Z_{ij} is a vector of explanatory variables associated with the technical inefficiency effects, τ_0 is the constant of the technical inefficiency model, and is a vector of unknown parameter to be estimated (Bai et al., 2016).

Equation (21) can be transformed into:

$$\ln(D_I^t(X_i^t, Y_i^t, t)) = u_i - v_i \tag{23}$$

The distance function possesses the characteristic of homogeneity, which means that the normalization for a certain input can be written as:

$$\begin{aligned} &D_I^t(X_i^t / x_n, Y_i^t, t) = D_I^t(X_i^t, Y_i^t, t) / x_n \\ &\Rightarrow -\ln x_n = \ln(D_I^t(X_i^t / x_n, Y_i^t, t)) - \ln(D_I^t(X_i^t, Y_i^t, t)) \end{aligned} \tag{24}$$

According to equations (23) and (24), we can generate

$$-\ln x_n = -\ln(D_I^t(X_i^t / x_n, Y_i^t, t)) - u_i + v_i \tag{25}$$

Technical efficiency (TE) can be estimated by equation (25). It is defined as the ratio of the observed output to the corresponding potential output given the production frontier (Song et al., 2013), specified as

$$Y_i = f(X_i, \beta)\exp(v_i - u_i) \tag{26}$$

Therefore, the technical efficiency is written as equation (27).

$$TE_i = \frac{f(X_i, \beta)\exp(v_i - u_i)}{f(X_i, \beta)\exp(v_i)} = \exp(-u_i) = \frac{1}{D_I^t(X_i^t, Y_i^t, t)} \tag{27}$$

We also included two additional indicators, the EPI and the EE. The EPI is defined as the ratio of the distance function values obtained from the production function incorporating the ecological input to those without ecological input. The EPI is then written as follows:

$$EPI_i = \frac{D_I^t(X_i^t \quad eco, Y_i^t) - D_I^t(X_i^t, Y_i^t)}{D_I^t(X_i^t, Y_i^t)} = \frac{TE_i^t(X_i^t \quad eco, Y_i^t) - TE_i^t(X_i^t, Y_i^t)}{TE_i^t(X_i^t, Y_i^t)} \quad (28)$$

The EE is defined as the ratio of minimum feasible ecological input use to observed ecological input use, conditional on the observed levels of the other input and outputs (Reinhard et al., 1999).

$$EE_i = \frac{\min.feasible \quad eco\log ical \quad input}{observed \quad eco\log ical \quad input} \quad (29)$$

The output distance function is defined similarly:

$$D_O^t(X^t, Y^t) = (\sup\{\lambda : (X^t, \lambda Y^t) \in S^t\})^{-1} \quad (30)$$

This function is defined as the reciprocal of the 'maximum' proportional expansion of the output vector Y^t, given input X^t. We can choose either of the two functions considering the requirement. Specifically, the ecological input in Shandong is built-up area (BUA). The land input is all cultivated land in these two regions. The regional eco-efficiency in Shandong can be calculated as follows,

$$X_S^t = (cultivatedarea, NPP, capital, labor, property1, property2, \ldots) \quad (31)$$

$$Y_S^t = (land \quad productivity) \quad (32)$$

$$\begin{cases} -\ln x_n = -\ln(D_I^t(X_i^t(NPP_i)/x_n, Y_i^t, t)) - u_i + v_i \\ -\ln x_n = -\ln(D_I^t(X_i^t(\widehat{NPP}_i)/x_n, Y_i^t, t)) - \overline{u_i} + v_i \end{cases} \quad (33)$$

Besides, there are the land-use based trade-offs of ecosystem services between NPP, cropping returns and urbanization identified by sizes of built-up area within each pixel. This means that the different trade-offs can be embodied in the indicator of EE calculated by NPP based on the ESLP model. And the EE is then written as follows:

$$EE_i = \frac{min.feasible\ NPP_i}{NPP_i} \tag{34}$$

4 Results and analysis

4.1 Analysis on estimated land productivity

The land productivity of Shandong during 1990–2010 was estimated based on the ESLP. To validate the estimated results, we compared the statistical grain yield with the estimated average land productivity in 110 counties in Shandong (Fig. 5). The correlation analysis results showed that there existed significant correlativity between statistical grain yield and ESLP estimated land productivity (at 5% significance level), indicating that land productivity estimated by the ESLP can indicate agricultural productivity at some extent in Shandong.

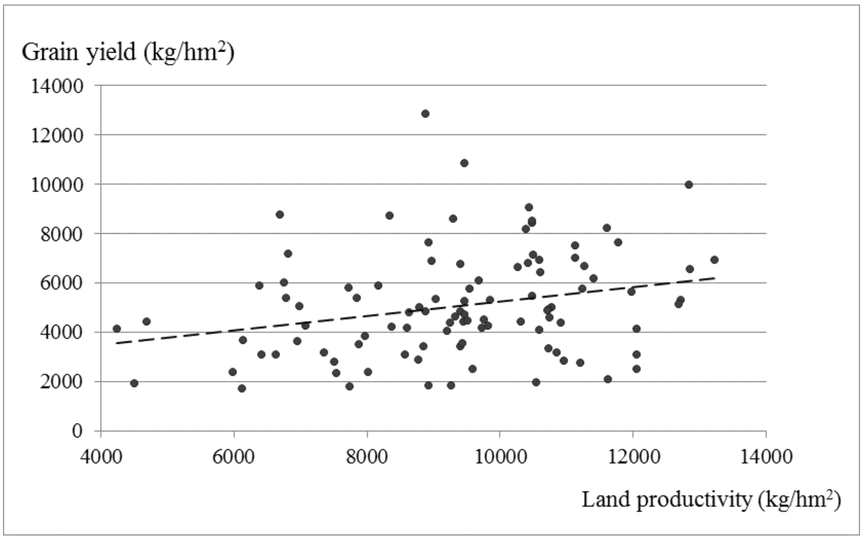


Fig. 5 Correlation analysis of grain yield and land productivity in Shandong

The spatial pattern of land productivity showed an unevenly distribution in Shandong, with higher values in the west and lower values in the east, which was closely related with land use/cover patterns (Fig. 6). For example, where the pixel was covered by built-up land or water areas, the land productivity there was almost low to zero, while if the pixel was covered by grassland, forest land or cultivated land, the values of land productivity were higher to>10,000 kg/hm2. According to pixel-level statistics, more than half of the pixels possessed land productivity values that were higher than the average value in Shandong. Especially, pixels with land productivity values of above 10,000 kg/hm2 accounted for around one-quarter of the total area.

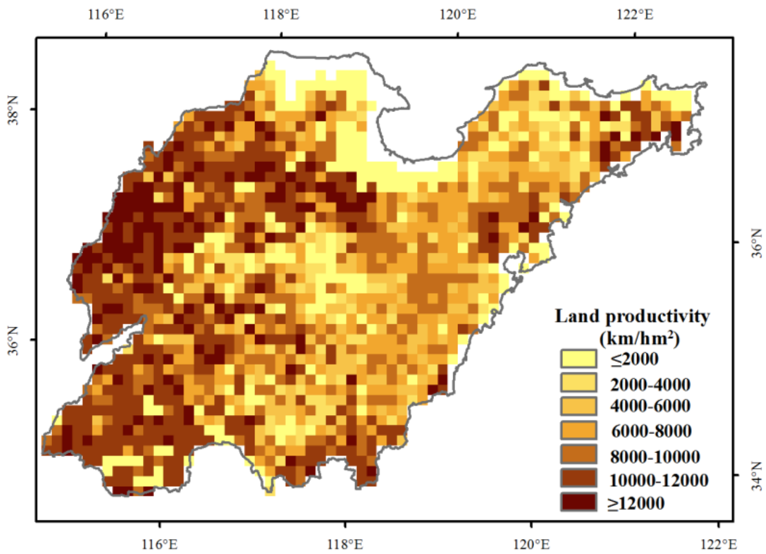


Fig. 6 Mean annual average land productivity in Shandong during 1990-2010

4.2 Analysis on eco-efficiency

Based on the SFA, we calculated the regional eco-efficiency in Shandong. The eco-efficiency of 17 cities in Shandong is shown as in Table 1 and Fig. 6. The non-constrained results of the SFA were proved to be more accurate than the constrained model to express the eco-efficiency of Shandong. From Table 1 and Fig. 6, we can conclude that the eco-efficiency of most cities in Shandong was relatively high at over 0.9, including Linyi, Laiwu, Liaocheng, Zibo, Yantai, Qingdao, Jinan, Jining, Heze, Dongying, Weifang, Rizhao and Tai’an. Most of these cities were in the zones with developed cities, ecological tourism, or belonging to the coastal economic zone and mountainous areas. Conversely, only Weihai, Zaozhuang, Dezhou and Binzhou remained in the low efficiency group (Fig. 7). The common feature in those cities was that they were far away from the provincial center or economic center. In most cities, the values of EPI were positive, which meant that the loss of vegetation contributed significantly to urbanization and social/economic development. However, the cities where EPI<0 indicated that the relationship between the ecological environment and economic growth was small.

Table 1: City-level eco-efficiency in Shandong, 2010

Code	City	Eco-efficiency	EPI
1	Jinan	0.9823	0.0180
2	Qingdao	0.9740	0.0267
3	Zibo	0.9628	0.0386
4	Zaozhuang	0.8298	0.2051
5	Dongying	0.9949	-0.0051
6	Yantai	0.9647	0.0365
7	Weifang	0.9962	-0.0038
8	Jining	0.9889	0.0113
9	Tai’an	0.9975	-0.0025
10	Weihai	0.7563	0.3222
11	Rizhao	0.9970	-0.0030
12	Laiwu	0.9490	0.0538
13	Linyi	0.9316	0.0734
14	Dezhou	0.8385	0.1926
15	Liaocheng	0.9600	0.0416
16	Binzhou	0.8849	0.1301
17	Heze	0.9918	0.0082

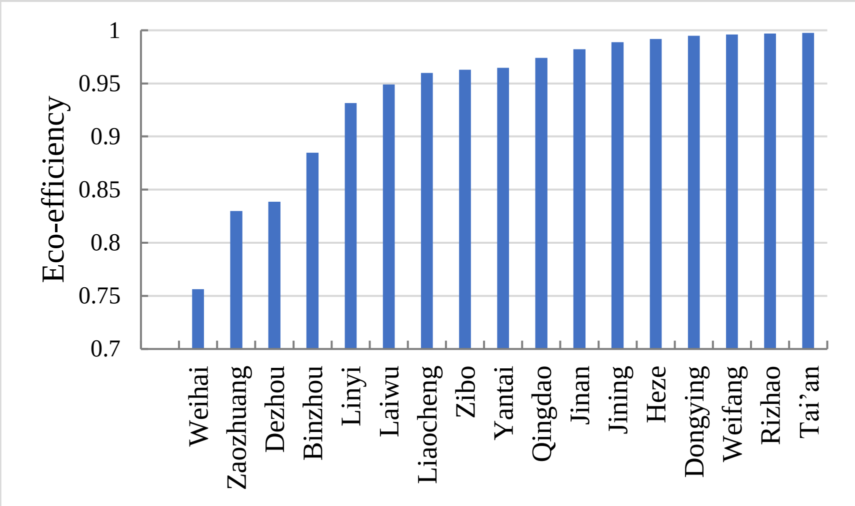


Fig. 7 City-level eco-efficiency ranking in Shandong, 2010

5 Conclusions and Discussions

In this study, with the support of large scale of multi-source data, including land use datasets, various observation datasets, socioeconomic statistics from yearbooks, and data produced by other projects, we estimated land productivity in Shandong during 1990–2010 using the ESLP. Then, we calculated the eco-efficiency of agricultural production in Shandong based on SFA. Our results showed that land productivity was unevenly distributed in Shandong and was relatively lower in regions covered by built-up area. The non-constrained results of SFA were proved to be more scientific than the constrained model to express the eco-efficiency of agricultural production in Shandong. The eco-efficiency of most cities in Shandong was relatively high at over 0.9. In most cities, the values of EPI were positive, which meant that the loss of vegetation contributed significantly to urbanization and social/ economic development.

Based on the estimation of land productivity and analyses of eco-efficiency of agricultural production, this paper can also provide evidence and suggestions with respect to sustainable agricultural development in Shandong. The results indicated that the land productivity was unevenly developed and some cities located far from the provincial economic centres were possessed with low eco-efficiency, which implies that to achieve sustainable agricultural production in Shandong, timely management of trade-offs between agricultural production and urbanization are needed, and the adjustment of agricultural technological measures according to specific local conditions will improve land productivity and eco-efficiency.

We quantitatively analyzed land productivity and eco-efficiency based on the ESLP and SFA, which was proved to be useful tools to evaluate eco-efficiency and to identify regional differences in agricultural development. However, our study had some limitations. There were uncertainties in some parameter values, which may reduce the accuracy of the estimated results. For example, land productivity is influenced by both natural factors and human activities, but more natural factors than human activities are considered in the estimation of land productivity in the ESLP, and it can be further improved by including the contribution of cultivated land conversions to land productivity in the future research.

Declarations of interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgements

This work was financially supported by National Natural Science Fund for Distinguished Young Scholar (Grant No. 71225005), National Natural Science Foundation of China (Grant No. 41771568), and the National Natural Science Foundation of International/Regional Cooperation and Exchange Programs (Grant No. 71561137002).

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Chapter 9: Conclusions

This thesis focuses on the trade-offs between ecosystem services, provided by natural capital, and certain land use and cover changes (LUCC) in China. One of the main changes is the conversion of land into urbanized, built-up area, and so this can be thought of as an example of substitution between natural capital and built capital. By better understanding the trade-offs between these types of capital, researchers and policy makers can better judge whether an economy is on a sustainable pathway. Of course, some of the specific trade-offs studied in this thesis, such as between grassland quality and livestock production, between landscape diversity and crop residues, and between urbanization and terrestrial net primary productivity (NPP) have also been a focus of many other papers by economists, and by other social and environmental scientists (e.g. Allen et al., 1991; Pearce & Moran, 1994; Geoghegan et al, 1997; Swinton et al., 2007; Hubacek et al., 2009; Stehfest et al., 2013; Deng et al., 2015).

A particular aim of this thesis was to look at the impacts on the socio-economy from the dynamics of LUCC in China and to see effects of some policies and regulations adopted by central and regional governments to preserve or restore ecosystem services. Therefore, in this thesis I assess trade-offs between land use/land cover change (LUCC) and ecosystem services in three case study areas (Hebei, Qinghai, and Shandong provinces). The lessons learned from exploring these case studies may help to improve the optimal management of ecosystem services and to support socio-economic development. More generally, by studying these cases it may be possible to contribute to the literature that seeks to improve policy-oriented optimum land-use management in order to restore or enhance ecosystem services.

Looking through the history of land use policies in China, a milestone mark was the reform and opening-up policy during 1978-1982 (Ding, 2003). With the beginning of the Household Responsibility System in 1978, where rural households could partially farm on their own account, there was a series of China's land use policies that clarified property rights, resulting in People's Republic of China Land Management Law (Revision) in 1998 (Gong, 2018). This policy has moved rural China away from the planned economy approach, and thereby has made the role of land use policy more important to ecological restoration in China. Under the earlier central planning approach, command-and-control methods may have been used, but in the more market-oriented approach, the response of individual cultivators and livestock herders (which can be thought of, generally, as family farmers) to policies that regulate land-use becomes important to understand. This change also makes the lessons from China more applicable to other countries that tend to rely on individual agents to respond to incentives rather than on the command-and-control approach of central planning.

Policy and environmental planning decisions may influence how land is being managed. Land management, as defined by the presence of human activities, covers a range of issues such as ecosystem exploitation, land use management, and ecosystem management, and this affects land cover directly and indirectly. In this research, the trade-offs between ecosystem services, and certain land use and land cover changes (LUCC) have been studied. To make the study manageable, the regional problems in three regions that typify issues facing China — Qinghai, Hebei and Shandong provinces — to specifically analyze the trade-offs between ecosystem services and activities such as urban expansion that caused the local LUCC. To be more specific, the relationships between grassland quality and livestock production, between landscape diversity and crop production, and between urbanization and terrestrial net primary productivity (NPP) have been explored for Hebei, Qinghai and Shandong provinces, respectively. With better understanding of these trade-offs, and of the effect of land-use practices and management for conserving ecosystem services, the thesis may contribute to the literature on the optimum management for sustaining ecosystem services.

Chapter 2 reviews analytical tools and approaches used to study trade-offs in ecology, economics and other fields. It concludes that it is critical to conduct trade-off analysis of ecosystem services that may be affected by changes in land uses. Explicit recognition of trade-offs and their importance for the long-term sustainability of ecosystem services is important to help policy-makers to gain a better understanding of the choices they face and the corresponding consequences (Gascoigne et al., 2011; Deng, Li, & Gibson, 2016).

Chapter 3 proves a case study on the effects of landscape diversity. This diversity interprets has both ecological significance and economic significance through influencing land use patterns. The impact of landscape diversity upon crop production can also be represented as an ecological effect, which provides indirect effects on economic production associated with cultivated land changes (Deng, Gibson, & Wang, 2017a). These ecological effects on economic production are key to some of the trade-offs studied throughout this thesis.

Chapter 4 provides a case study of sustainable land use management for improving regional eco-efficiency, where this is important because of the economic significance of ecosystem services. Cultivated land is a key factor affecting crop production, which is positively correlated with crop yields. Although the land use management system implemented by the Chinese government seems to be effective, there are still some regions within the case study area that are of concern because of their lower values of eco-efficiency and their high elasticity of landscape diversity in response to changes in land use (Deng & Gibson, 2018a).

Chapter 5 provides a case study of quantitatively measuring the interaction between net primary productivity (NPP), as a measure of ecosystem health, and livestock production. In the case study area (Qinghai province) livestock production appears to be positive affected by variation in NPP, while grazing activity has an opposite effect on NPP. Consequently, there are direct and indirect effects of grazing management, in increasing livestock production but degrading grassland quality (in terms of NPP), and so there is still some potential for the further adjustment of the livestock industry, particularly through establishing appropriate grazing densities. There also appears to be a positive effect of ecological reserves, which may become increasingly important because climate change is expected to be an important influencing factor on NPP, which in turn links to livestock production (Deng, Gibson, & Wang, 2017b).

Chapter 6 uses remote sensing data, for 1km × 1km grids in Shandong province, to examine the management of trade-offs between the conversions of cultivated land to non-agricultural (primarily urban) use and land productivity. It appears that spatial variation in land productivity reflects the growth in built up area, with lower productivity in regions of the province where cultivated land was converted to other uses over the 1985-2010 study period. While expansion of built-up area is threatening land productivity, cultivated land conversion is still carrying on and so the trade-offs identified in this chapter will be on-going issues for land management in coastal provinces of China (Sutton et al., 2016; Deng, Gibson and Wang, 2017c).

Chapter 7 aims to discover potential trade-offs between one form of built capital – transport infrastructure, and specifically whether roads are acting more like "pressure cookers"—and are associated with lower levels of cultivated land and greater rates of cultivated land loss in the case study area of Shandong province. It indicates that there is no evidence to suggest that roads are creating pressures on cultivated area. Since roads are crucial to the socio-economic development strategy, and the road is a form of produced capital, the lack of apparent trade-off means that at least for this special case, China may not exhaust natural capital faster than producing built capital (Deng, Gibson, & Jia, 2017d).

Chapter 8 indicates the existence of trade-offs between agricultural production and urbanization, as revealed by the use of Stochastic Frontier Analysis in the case study region. There is spatial variation in land productivity, with prefectures located far from the provincial economic centers in Shandong having lower eco-efficiency. This implies that to achieve sustainable agricultural production in this province, timely management of trade-offs between agricultural land use and urbanization are needed. Moreover, the adjustment of agricultural technological measures according to specific local conditions will improve land productivity and eco-efficiency (Deng & Gibson, 2018b).

Each of these case studies use different methods, ranging from simple regression to matching methods and stochastic frontier analysis. Likewise, a range of data are used, from very detailed remote sensing data on land cover and changes in land cover at the one-kilometer square pixel level, to more aggregated administrative data at county and prefecture level. However, a unifying theme throughout the case studies is a quest for a better understanding of the optimum management needed to sustain ecosystem services and support socio-economic development. In conjunction with prior studies on incorporating ecosystem services into economic management and policy discussion (Sanchirico et al., 2005; de Groot, 2006; de Groot et al., 2010; de Lange et al., 2010), the research in this thesis provides some suggestions on improving the understanding of the economic forces that affect, and the contributory role of, ecosystem services. Within the broader environmental economics concept of weak sustainability, the case studies in the thesis all involve trade-offs between natural and produced capital, especially in the form of the built urban environment. These are trade-offs that are increasingly apparent as countries such as China undergo rapid urbanization with associated changes in land cover and in land use which puts pressure on ecosystem services.

There are many limitations of this study, and not just because the case studies cover only three of China's provinces. There are uncertainties due to some parameter values, which may reduce the accuracy of the estimated results, even though the same style of modelling and data could be used elsewhere for analyzing the changing trends in land productivity and can provide valuable decision support information for land-use planning and land-use management. Nevertheless, it is still necessary to carry out some further research, for example, this study has not estimated the accurate contribution of cultivated land conversion to the change in land productivity (Jiang et al., 2011). Moreover, land productivity is influenced by both natural factors and human activities, but more natural factors are considered in the estimation of land productivity (Deng et al., 2006), and the study can be further improved by involving the contribution of cultivated land conversions to land productivity in the future research. In addition, the future research needs to be concentrated on the examination of the land-use practices and management for conserving ecosystem services as well as for advancing human well-being. More such studies will contribute to the existing literature on how the LUCC-induced ecosystem service changes exert impacts on human well-being, which can then help with achieving a sustainable environment and economic development.

As a final note, more and more attention in the scientific literature has been paid to the close relationship between the evolution of the natural environment, the terrestrial ecosystem process, the human production activities and the dynamics of the land system changes. This literature involves work both by environmental economists, by ecologists, and by researchers from disciplines concerned with land use management. In addition to contributing to this literature, the studies in this thesis can also be used to examine a triple challenge: the inter-linked interactions between LUCC, ecosystem services, and human well-being at both local and regional extent. Armed with this enhanced knowledge, future research can further identify the dominant influence of land-use management policies on ecosystem services and human well-being.

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