Journal of Cleaner Production 142 (2017) 767–774

Contents lists available at ScienceDirect

Journal of Cleaner Production

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

Management of trade-offs between cultivated land conversions and land productivity in Shandong Province

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A R T I C L E I N F O

Article history:
Received 31 October 2015
Received in revised form
11 April 2016
Accepted 12 April 2016
Available online 20 April 2016

Keywords:
Land productivity
Land use
Land conversion
Data fusion

A B S T R A C T

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 1 km × 1 km grid cell in Shandong Province. Then land productivity in the study area is assessed with the Estimation System of Land Production (ESLP) model 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.

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 °C 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-

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http://dx.doi.org/10.1016/j.jclepro.2016.04.050
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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 34 123 km^2 to 39 110 km^2 during 1988–2008, but meanwhile the cultivated land area decreased from 83 623 km^2 to 80 135 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 slow down 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?

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 Estimation System of Land Production (ESLP) model, which integrates multi-source data into different forms of indices to calculate land productivity. Fourthly, cultivated land conversion data and land productivity data in 1 km × 1 km 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 (2014) 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, 2008; 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

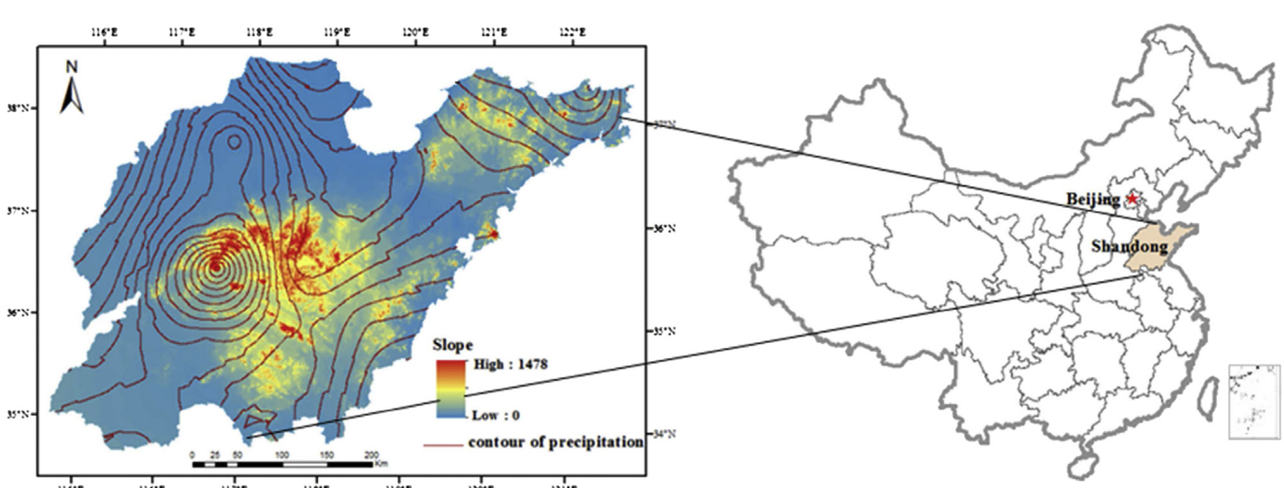

Fig. 1. Location and mean annual rainfall of the study area of Shandong Province.

is an early exercise to apply land evaluation at a continental scale (FAO, 1978). The ESLP model assesses land productivity based on the agricultural ecology zone. Compared with other models, ESLP model 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 model 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 is the new mega-rich of Silicon Valley at first, harnessing data from 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 socio-economic 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., 2008a).

One-kilometer 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., 2010b). 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. One-kilometer 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 1 km $\times$ 1 km grid scale based on the fusion of socio-economic data and geographic data. The LUCC can be identified on the 1 km $\times$ 1 km$\times$1 km grid scale, and the 1-km area percentage data model is introduced in this study to trace cultivated land conversions at the 1 km $\times$ 1 km grid level. One-kilometer 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 1 km $\times$ 1 km 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 1 km $\times$ 1 km 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. One-kilometer 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 the ESLP model. The ESLP model is conducted on the basis of agro-ecological 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 and temperature productivity, climatic productivity, soil productivity, land productivity.

Firstly, photosynthetic productivity is expressed as follows.

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

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, ε 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 and temperature productivity.

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

where Y_{lt} (Unit: kg/hm^2) is the light and temperature productivity, which refers to agricultural productivity determined by light 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: °C) represents the average temperature in a certain period, T_0, T_1, and T_2 (Unit: °C) 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.

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

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:

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

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.

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

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).

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

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.

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

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. $\varnothing$ (Unit: kPa P^{-1}) is the psychrometric constant, T' (Unit: °C) is the mean daily air temperature, u_2 (Unit: ms^{-1}) is the wind speed at 2 m 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).

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

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 ESLP, changes of land production of each 1-km cell can be written as follows.

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

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 is 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, socio economic 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 and temperature productivity of cultivated land.

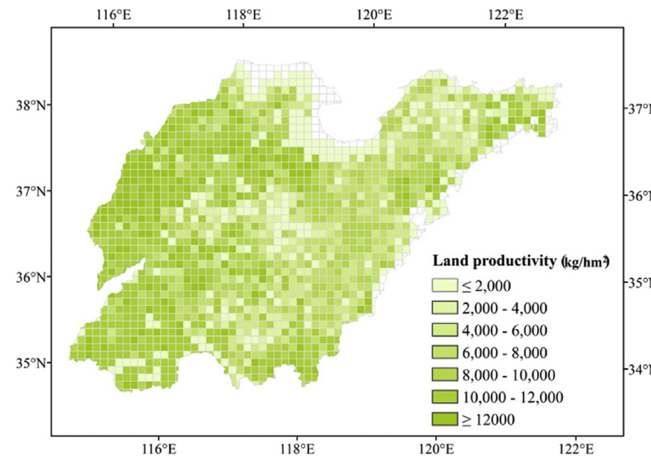

Fig. 2. Estimated multi-year average land productivity based on annual observed data during 1985–2010 in Shandong Province.

4. Results

4.1. Spatial distribution of land productivity

4.1.1. Estimation of land productivity

The estimation results from the ESLP model 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 (Figs. 2 and 3). In addition, the results show that the land productivity ranged from zero to 13 957 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 10 000 kg hm^{-2} to 12 000 kg hm^{-2} accounted for 23.5% of the total area (Fig. 4).

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 Mean daily temperature Daily maximum temperature Daily minimum temperature	Precipitation Relative humidity Precipitation intensity Precipitation variation	Sunshine hours PAR	Soil texture Soil fertility Erosion intensity	Land use structure Land use intensity	Wind speed Saturation vapor pressure Actual vapor pressure

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

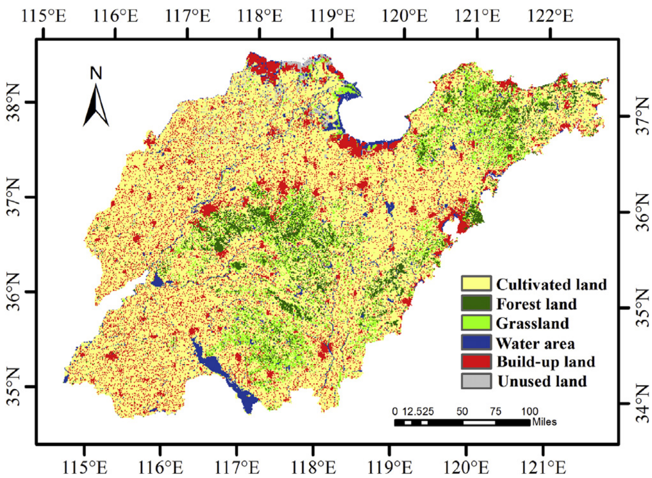

Fig. 3. Land use/cover map of Shandong Province in 2008.

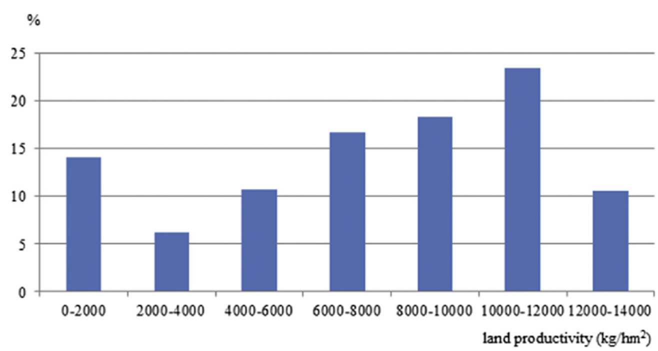

Fig. 4. Interval distribution of multi-year average land productivity during 1985–2010 in Shandong Province.

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 from the ESLP model. The validation results show that land productivity from the ESLP model is significantly correlated with grain yield ($R^2 = 0.63$, $p < 0.01$), indicating that land productivity estimated by ESLP model can be used to represent the agricultural productivity (Fig. 5).

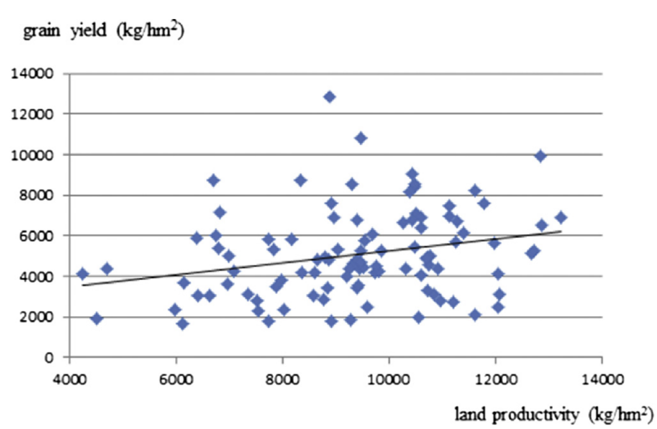

Fig. 5. Relationship between land productivity estimated by ESLP and grain yield in Shandong Province.

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 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.

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 27 583 hm^2 and 34 910 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 using the ESLP model. 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

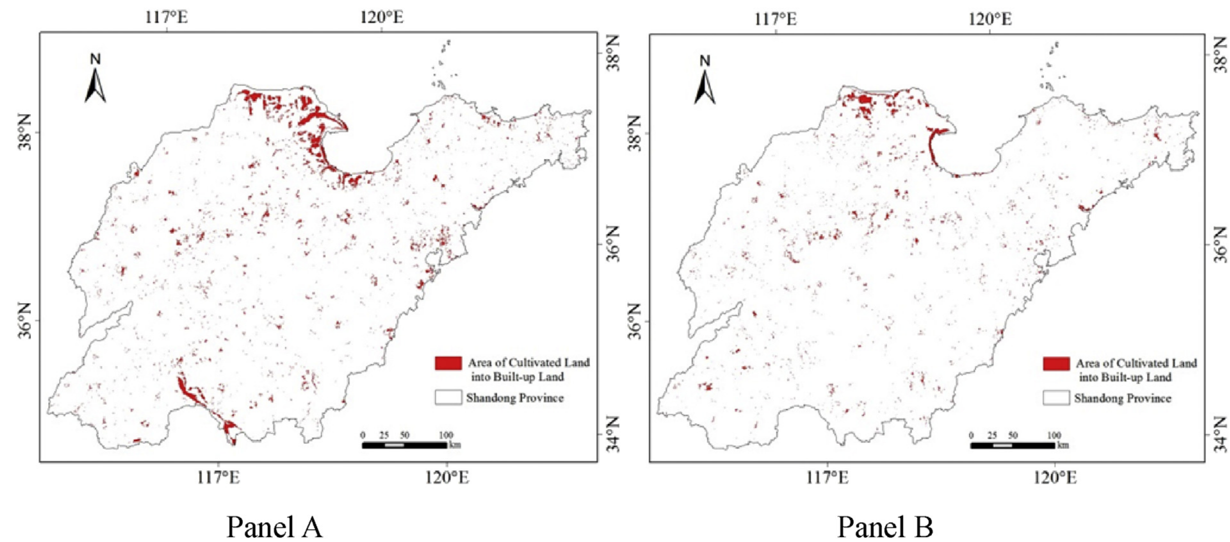

Fig. 6. Land conversions between cultivated land and built-up land: Panel A and B depict the cultivated land transformed into built-up area during 2000–2005 and 2005–2010, respectively.

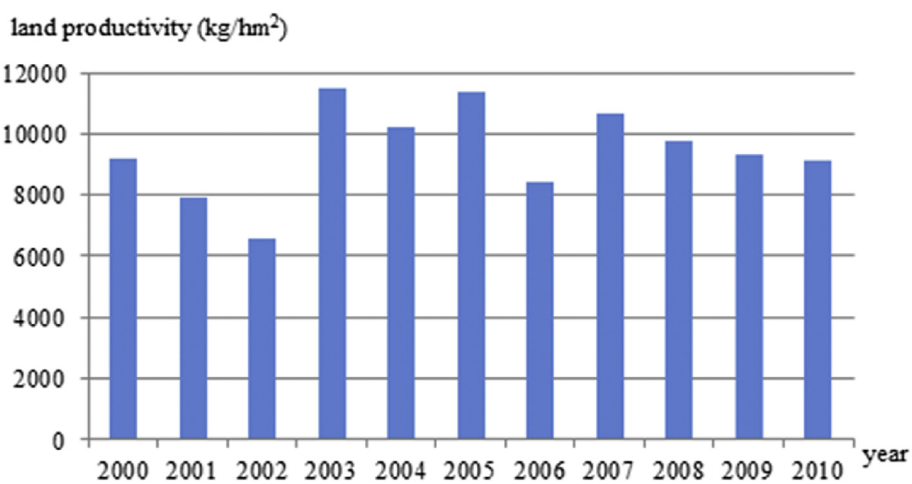

Fig. 7. Land productivity in Shandong Province during 2000–2010.

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 model which is capable of the identification of substitutability between each of land use types and crop types as well. 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 model 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 in the ESLP model, and it can be further improved by involving the contribution of cultivated land conversions to land productivity in the future research.

Acknowledgments

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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