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Farmland fragmentation due to anthropogenic activity in rapidly developing region

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ABSTRACT

Measuring farmland fragmentation and its interactions with anthropogenic activities can advance our understanding of complexity in agricultural systems. Majority of previous studies focused on farmland ownership fragmentation rather than physical landscape fragmentation. This paper characterized the farmland landscape fragmentation dynamics in Tiaoxi watershed (China) from 1985 to 2013 using a set of variables (area-weighted mean patch area, patch density, area-weighted mean shape index, mean Euclidean nearest neighbor distance, splitting index, and effective mesh size). Four categories of anthropogenic drivers (demographic, economic, social and cultural, and scientific and technological) and their relative importance were quantified by multiple regression and variance partitioning. Results showed a linear increasing trend of farmland fragmentation in Tiaoxi watershed during the study period. Drivers for farmland fragmentation differed with variables. In general, non-agricultural population and migration population were the key demographic drivers, while road mileage and investment in real estate were the principal social drivers. Two groups of economic drivers were identified: one group included fruit and seafood production, another included per capita income and proportion of tertiary industry. Besides, education expenses increases and technological improvement could significantly reduce farmland fragmentation. Considering the relative importance for different categories of drivers, economy was the most influential driver; its joint influences with social and cultural drivers and those with scientific and technological drivers were relatively stronger. Our study advanced the understanding of principle anthropogenic drivers influencing farmland fragmentation dynamics.

1. Introduction

Farmland supplies primary products and performs a variety of ecosystem services (Schipanski et al., 2014). It provides habitat for wildlife, regulates local climate, maintains biodiversity, absorbs pollutants, controls soil erosion, and offers recreational opportunities for urban dwellers (Zasada, 2011). Ironically, though farmland is widely acknowledged as a significant contributor to regional sustainability, it is completely susceptible to the dramatic land use transformation driven by anthropogenic activities. Such general perception is on the basis of numerous cases and anecdotal observations regarding anthropogenic impacts on farmland. It is reported that farmland has been experiencing various degradation processes, including depletion, contamination, declined productivity, and fragmentation (Bakker et al., 2011; Nabulo et al., 2012; Müller et al., 2013; Su et al., 2012).

Fragmentation refers to the process that entities supposed to be cohesive for optimally functioning are segregated in space (Carsjens and van Lier, 2002). Farmland fragmentation issues are two-folded—the issue of landscape physical fragmentation and the issue of land use ownership fragmentation (Brabec and Smith, 2002; Farley et al., 2012). Landscape physical fragmentation refers to it that the number of farmland patches increases and their patch size decreases. Land use ownership fragmentation denotes the situation that plots managed by one household are spatially separated (McPherson, 1982). Ownership fragmentation can lower the production efficiency and increase management costs (Tan et al., 2006), presenting great potential for future landscape physical fragmentation (Farley et al., 2012). Majority of previous studies focused on the ownership fragmentation rather than the farmland landscape fragmentation (Demetriou et al., 2013; Sikor et al., 2009;

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Tan et al., 2006). Landscape physical fragmentation is tightly linked with a number of ecological processes (Llausàs and Nogué, 2012; Uuemaa et al., 2013). Measuring farmland landscape fragmentation and its interactions with anthropogenic activities can advance our understanding of complexity in agricultural systems. We therefore argue that it is a worthwhile goal to characterize the dynamics of farmland landscape fragmentation and the corresponding anthropogenic drivers. However, rather few efforts have been made in this regard.

Landscape ecology offers theory basis and a diversity of variables for description of landscape fragmentation (e.g., effective mesh size, landscape division index, splitting index, patch density, etc.). Long time series of farmland information can be obtained from remotely sensed imageries (Brown and Pervez, 2014; Lobell et al., 2007; Yan et al., 2013). The comprehensive employment of remote sensing, landscape ecology, and geographical information systems (GIS) has been widely applied in agricultural systems modeling and management (Maeda et al., 2010; Sayer et al., 2013). Objectives of this paper are to investigate farmland fragmentation dynamics and the corresponding anthropogenic drivers using a landscape ecological approach, combined with remote sensing and GIS. Farmland fragmentation here refers to the landscape physical fragmentation instead of land use ownership fragmentation.

2. Materials and method

2.1. Study area

The Tiaoxi watershed, which is a part of the Taihu Lake drainage area, is located in the middle part of Chinese eastern coast (Fig. 1). Extending from 119°14′E to 120°13′E and from 30°07′N to 31°11′N, this watershed lies within the subtropical climate zone, characterized by long summer and winter seasons, but short spring and autumn seasons. Paddy soils are fertile and occupy a large part of the total area. The climatic and soil conditions are beneficial for grain production. The high grain yields make Tiaoxi watershed a regional important agricultural production base.

Tiaoxi watershed belongs to the Yangtze River Delta Economic Development Zone, which is the most developed and populous region in China. It has been experiencing rapid socioeconomic development and agricultural commercialization since the 1980s. Profound built-up land expansion has been driven by the booming socioeconomic development (Su et al., 2011). Many farmers also converted their cropland into gardens and artificial ponds. These land use changes significantly altered the structure and pattern of farmland systems. Thus, the case of Tiaoxi watershed is a good reference for the characterization of anthropogenic drivers for farmland fragmentation.

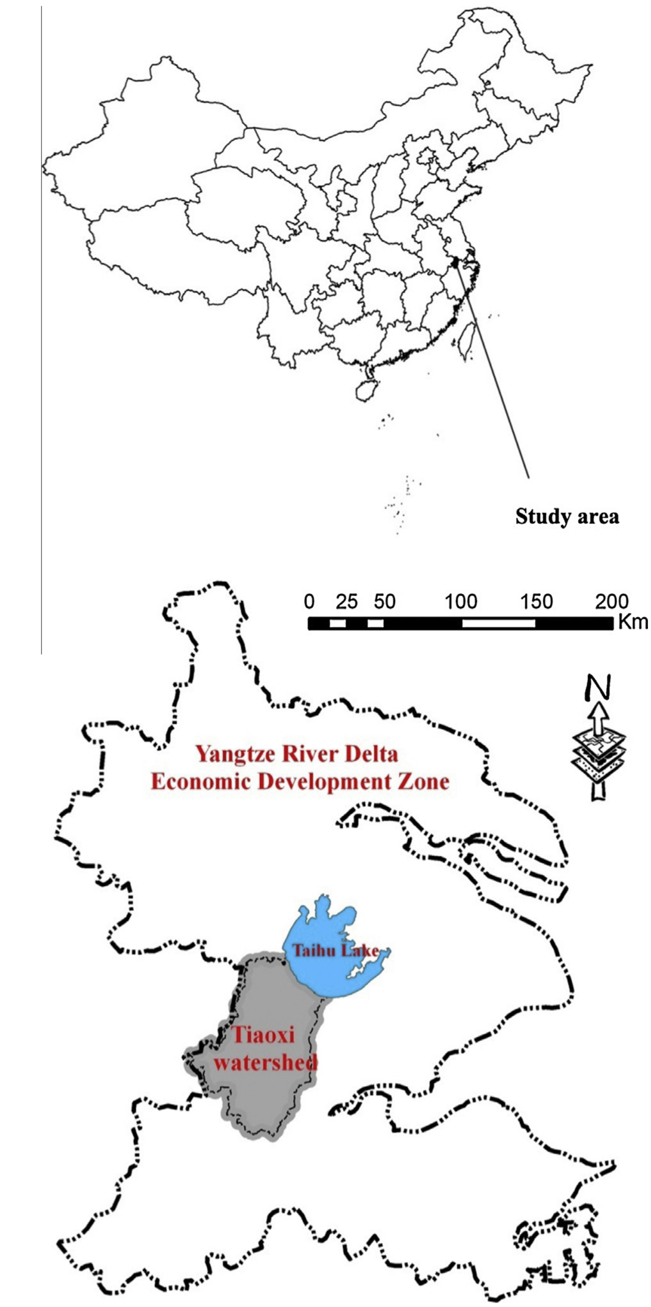

Fig. 1. Location of the Tiaoxi watershed within the Yangtze River Delta Economic Development Zone, China.

2.2. Image classification

Farmland in the study area included paddy and dryland. The farmland information from 1985 to 2009 was from Su et al. (2014a), which was based on China–Brazil Earth Resources Satellite images (2004, 2006 and 2007), Landsat Enhanced Thematic Mapper images (1999, 2000, 2001, 2002, and 2003), and Landsat Thematic Mapper images (1985, 1994, 2005 and 2009). Farmland information in 2013 was visually interpreted based on Landsat Operational Land Imager (OLI). The final farmland maps were displayed in Fig. 2.

2.3. Metric selection

Farina (1998) pointed that landscape fragmentation was closely related to patch size, edge, shape, connectivity, and isolation. We first collected a set of 51 class level landscape metrics based on literature review, and used varimax rotated principal component analysis to reduce redundancy (Plexida et al., 2014; Su et al., 2014b). Finally, six variables were selected to describe farmland fragmentation, including area-weighted mean patch area (AREA_AM), patch density (PD), area-weighted mean shape index (SHAPE_AM), mean Euclidean nearest neighbor distance (ENND_MN), splitting index (SPLIT), and effective mesh size (MESH). These variables represent the areal and shape characteristics, connectivity, as well as division degree among farmland patches.

2.4. Selection of potential anthropogenic drivers

Scholars have developed a number of variables to indicate anthropogenic activity, such as urban land expansion, road density,

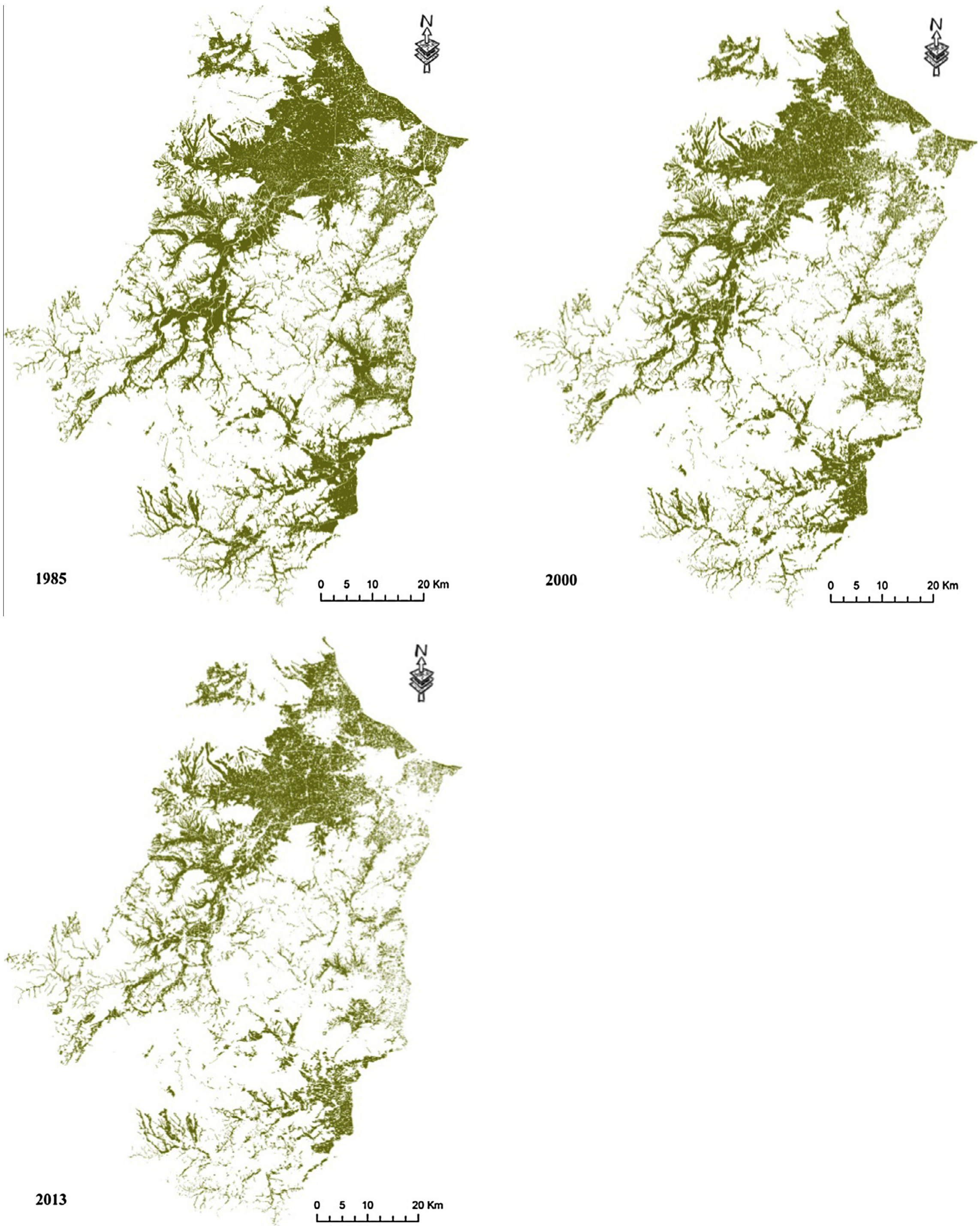

Fig. 2. Farmland patterns from 1985 to 2013 in Tiaoxi watershed, China.

proximity to city, energy consumption, population density, GDP, passenger volume, investment, and many other socioeconomic variables (Gong et al., 2013; Ma et al., 2012; Pert et al., 2012; Su et al., 2011). Nelson et al. (2006) reviewed the literature and divided the anthropogenic drivers of ecosystem change into four categories: demographic drivers, economic drivers, social, political and cultural drivers, scientific and technological drivers. Variable selection followed this framework and considered data availability. We were accessed to the official statistical database by the local government. All the selected variables were annually recorded at community level.

Population dynamics are usually described from two aspects: current population conditions and primary determinants (Nelson et al., 2006). Five variables were therefore selected to indicate demographic drivers: population density (Pop_D), non-agricultural population proportion (NPop_P), birth rate (Bir_R), mortality rate (Mor_R), and migration population proportion (MPop_P).

Economic activity is not only in the form of economic growth, but also embodied by structural transformation and consumption pattern changes. GDP and per capita income (Inco) were the most popular indicators of economic growth (Gong et al., 2013; Martinelli et al., 2011; Schneider et al., 2011; Su et al., 2014b).

Proportion of secondary industry (PSIn) and the proportion of tertiary industry (PTIn) were usually used to describe economic structural transformation. Product accorded with demand in most cases, and can indirectly indicate consumption patterns. For eastern coastal China, farmland was converted to orchards and artificial ponds, in order to meet the increasing demand for fruit, tea, and seafood. Three production variables were therefore chosen: total fruit production (TFPr), total tea production (TTPr), and total seafood production (TSPr). Considering that globalization was also a typical economic phenomenon, the total export value (TEVa) was selected.

Social, political and cultural drivers always present fluid boundaries, and they change with observers, level of analysis and time (Young, 2002). Daily life requires the construction of the living and physical infrastructure, which would exert large impacts on ecosystems. We selected five variables to indicate social activities: investment in primary industry fixed assets (InFA), road mileage (RM), investment in real estate (InRA), passenger volume (PVo), freight volume (FVo). 'Household Responsibility' remained as the prevailing land use policy in China since the early 1980s (Krusekopf, 2002). No dramatic shift in land use policy occurred during the study period. Policy drivers were therefore not considered. Culture conditions reflected individual's perceptions and behaviors. Knowledge directly influences perceptions and behaviors. We therefore used the education expenses (EEx) and number of persons involved in education (NPEd) as cultural drivers.

Given the scientific drivers, we selected two variables: number of research people (NRP) and research expenditure (RE). We also picked three variables to indicate the technological improvement associated with farmland management: proportion of farmland ploughed by tractors (PFTr), proportion of effective irrigation area (PEIr), and proportion of farmland with high yields irrespective of drought or water logging (PFYi).

2.5. Multivariate statistics

Stepwise multiple linear regression analysis was applied to identify the anthropogenic drivers of farmland fragmentation. For each regression, one fragmentation metric acted as independent variable, and the selected potential anthropogenic drivers were the predictors. Before performing regression, all the predictors were normalized and standardized by the standard deviation model. The variance partitioning (VP) method was further employed to compare the relative importance of identified drivers. VP can decompose the variances for dependent variable into shares explained by individual or joined predictors (Anderson and Gribble, 1998; Heikkinen et al., 2005). In particular, the total explained variances, (R^2), were decomposed into several fractions: (1) unique influences of individual category of drivers (demographic, economic, social and cultural, scientific and technological); (2) joint influences of two categories of drivers; (3) joint influences of three categories of drivers; and (4) joint influences of four categories of drivers.

3. Results

3.1. Dynamic changes of farmland fragmentation

Fig. 3 showed the dynamic changes of the six fragmentation variables. PD, SHAPE_AM, and SPLIT presented increasing linear trend, while AREA_AM, ENND_MN and MESH exhibited declining tendency from 1985 to 2013. SHAPE_AM increased from 12.8 to 26.2, suggesting that farmland patches became more irregular. AREA_AM experienced a net decline of 82.5%, denoting that farmland area decreased on average. ENND_MN decreased from 114.3 to 103.2, signifying that connectivity among farmland patches was reduced. The growth of PD and SPLIT and decline of MESH implied that the division and subdivision degree was increased. All these results demonstrated that farmland fragmentation was intensified in Tiaoxi watershed during the study period.

3.2. Anthropogenic drivers of farmland fragmentation

Table 1 displayed the relationships between farmland fragmentation variables and anthropogenic activity indicators. More than 60% of the total variations were explained by the regression models. The explanatory ability and predictors differed with variables. No demographic factors were identified as significant predictor for

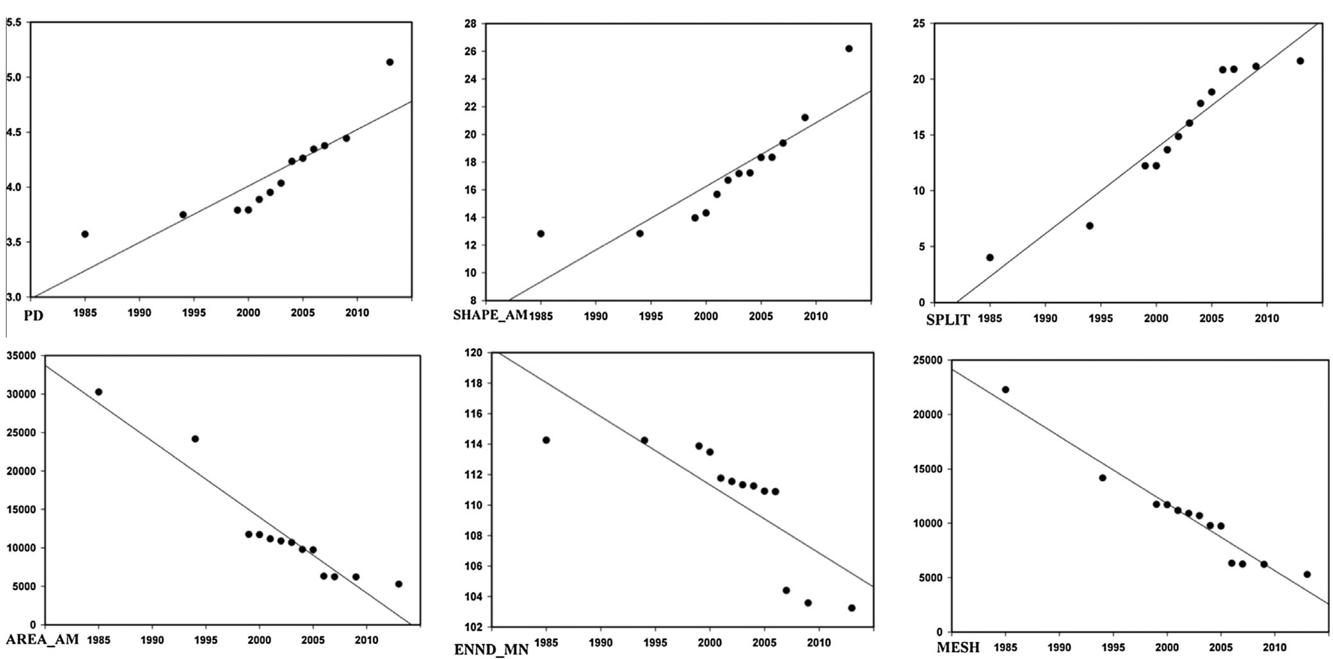

Fig. 3. Scatter-regression plot of farmland fragmentation metrics from 1985 to 2013. *Abbreviations:* area-weighted mean patch area (AREA_AM); patch density (PD); area-weighted mean shape index (SHAPE_AM); mean Euclidean nearest neighbor distance (ENND_MN); splitting index (SPLIT); effective mesh size (MESH).

Table 1
Anthropogenic drivers of farmland fragmentation identified by stepwise multiple regression.

Y	*X* (standardized coefficients)				R^2
	Demographic	Economic	Social and cultural	Scientific and technological	
AREA_AM		TFPr (−1.25), TSPr (−1.56)	InRA (−1.47), EEx (0.22)	PFTr (1.11)	.67[**]
PD	MPop_P (0.36)	Inco (2.21), PTIn (1.43)	RM (0.67), InFA (−0.13)	PFIr (−0.98)	.75[**]
SHAPE_AM		TFPr (0.78), TSPr (1.01)	InRA (0.35), InFA (−0.27)	PFTr (−0.45)	.70[**]
ENND_MN		TFPr (−0.11), TSPr (−0.26)	InRA (−1.15)	PFTr (0.62)	.64[**]
SPLIT	MPop_P (0.77)	Inco (1.59), PTIn (0.84)	RM (2.05), EEx (−0.37)	PFYi (−1.43)	.79[**]
MESH	NPop_P (−0.15)	Inco (−1.69), PTIn (−0.53)	RM (−1.94), InFA (0.59)	PFYi (1.44)	.77[**]

Abbreviations: Area-weighted mean patch area (AREA_AM); patch density (PD); area-weighted mean shape index (SHAPE_AM); mean Euclidean nearest neighbor distance (ENND_MN); splitting index (SPLIT); effective mesh size (MESH); migration population proportion (MPop_P); non-agricultural population proportion (NPop_P); per capita income (Inco); total fruit production (TFPr); total seafood production (TSPr); proportion of tertiary industry (PTIn); investment in primary industry fixed assets (InFA); road mileage (RM); investment in real estate (InRA); education expenses (EEx); proportion of farmland ploughed by tractors (PFTr); proportion of effective irrigation area (PEIr); proportion of farmland with high yields irrespective of drought or water logging (PFYi).
[**] $p < 0.01$.

Table 2
Influence of different categories of anthropogenic drivers in terms of their contributions to the total variations (%).[a]

	AREA_AM	PD	SHAPE_AM	ENND_MN	SPLIT	MESH
Demographic		2.9			2.0	1.7
Economic	**15.1**	**10.4**	**14.6**	8.6	**11.7**	**12.5**
Social and Cultural	9.4	8.3	8.5	**13.8**	9.7	9.4
Scientific and Technological	7.7	7.5	6.9	11.2	6.5	5.9
Demographic & Economic		3.3			3.5	2.4
Demographic & Social and Cultural		3.4			2.8	2.9
Demographic & Scientific and Technological		1.8			2.9	1.7
Economic & Social and Cultural	**25.6**	**19.1**	**26.5**	**18.7**	**19.9**	**17.4**
Economic & Scientific and Technological	**17.1**	**9.6**	**17.8**	10.5	**11.2**	**11.0**
Social and Cultural & Scientific and Technological	11.5	9.1	13.8	**22.6**	9.5	10.8
Demographic & Economic & Social and Cultural		4.1			3.9	3.6
Demographic & Economic & Scientific and Technological		4.5			2.8	3.0
Economic & Social and Cultural & Scientific and Technological	13.6	8.4	11.9	14.6	7.8	8.8
Demographic & Economic & Social and Cultural & Scientific and Technological		7.6			5.8	8.9

Abbreviations: Area-weighted mean patch area (AREA_AM); patch density (PD); area-weighted mean shape index (SHAPE_AM); mean Euclidean nearest neighbor distance (ENND_MN); splitting index (SPLIT); effective mesh size (MESH).
[a] Bold numbers denote the top three largest proportion.

AREA_AM, SHAPE_AM, and ENND_MN. Migration population growth would lead to increases in farmland fragmentation, since MPop_P was positively correlated with PD and SPLIT. MESH presented negative correlation with non-agricultural population proportion. As for the economic drivers, AREA_AM, SHAPE_AM, and ENND_MN had close relationship with fruit and seafood production, while the other variables were related to income and tertiary industry growth. Road mileage was significant social driver for PD, SPLIT, and MESH, and investment in real estate was the main social driver for the other three variables. The significance of cultural factor was pronounced for AREA_AM and SPLIT. Technology exerted significant influence on farmland fragmentation, since all the variables were correlated with technological indicators (PFTr, PEIr, and PFYi).

Contributions to the total variations by different categories of anthropogenic drivers were displayed in Table 2. Contributions of economic factors were higher than those of the other categories (AREA_AM, PD, SHAPE_AM, SPLIT and MESH). The joint influences between economic and social and cultural drivers, as well as those between economic with scientific and technological drivers were also quite strong. These results implied that economic factor was the most influential driver of farmland fragmentation. For ENND_MN, social and cultural factors shared larger proportion than the other categories. The joint influences between social and cultural factor and the other two categories of drivers were relatively stronger. Such results suggested that social and cultural factor was the main driver of farmland connectivity changes.

4. Discussion

Increasing demand for living and working space is expected as population grows (Long et al., 2009). Demographic factors therefore usually impact agricultural landscape patterns in an indirect way, mainly through urban growth (Su et al., 2011). However, the new population usually makes their living on existing facilities rather than on totally new departments and independent infrastructures (Shoshany and Goldshleger, 2002). Our study supported this argument, since population density was not a significant driver (Table 1). Population structure, non-agricultural population proportion and migration population proportion, in particular, had significant influence on farmland fragmentation (Table 1). The increase of non-agricultural population reflects a complex changing process of lifestyle. This process stimulates demand for more urban land, which intrudes into farmland and results in the occurrence of fragmentation. Many people flowed into cities in pursue of high income and urban life during the last thirty years in China (Yang, 2004). This migration process was accompanied by large scale farmland abandonment, which accelerated farmland conversion (Yang, 2004) and further led to fragmentation (Tan et al., 2006).

Our study identified two groups of economic drivers for farmland fragmentation: one group included fruit and seafood production, another were income and tertiary industry growth. The growth of per capita income changes the nature and level of persons' consumption, shifting from basic demand to services and goods that enhance life quality (Godfray et al., 2010). The share of tertiary industry rises as a consequence (Nelson et al., 2006). Tertiary industry development therefore indicates a complex transformation of service sectors and lifestyle (Nelson et al., 2006). It requires the growth of leisure sites and service infrastructure, whose development occupies a large amount of farmland, destroys the organization of farmland landscapes, and finally results in farmland fragmentation. Most farmers in Tiaoxi watershed acknowledged the profit of fruit and seafood, regarding fruit growing and seafood feed as high return land use choices. They converted farmland into orchard and artificial ponds. There lacked of regulated and scientific land use planning or guidance for the construction of orchard and artificial ponds from the local government. These orchard and artificial ponds were fragmented and irregular, and scattered in the farmland. Their disordered distribution divided original larger and intact patches into smaller and isolated patches, and finally fragmented farmland.

Extension of institutional and physical infrastructure is a common consequence of social advancement. Road construction can result in landscape fragmentation and further lead to declined connectivity (Fu et al., 2010). Our findings supported these arguments, since road mileage was significant social drivers for farmland fragmentation (Table 1). Investment in real estate also played critical role in fragmenting farmland (Table 1). The loss of farmland is common consequence of urban expansion (Su et al., 2011). Increasing investment in real estate promoted continuous construction of apartments and houses. Most new development in this watershed concentrated along transportation routes and areas with low slope, considering the physical suitability for expansion (Su et al., 2011). The new expansion occupied farmland, transformed the farmland landscapes, and gradually fragmented farmland within the watershed. Education expenses had negative correlation with SPLIT and positive correlation with AREA_AM. Education can improve farmers' knowledge and skills for more scientific tillage, helping to decrease farmland fragmentation.

The diffusion and advancement of knowledge and technology have critical implications for agricultural management, since they help reduce the human pressure on ecosystems (Nelson et al., 2006). Our discoveries supported this point, since technology was identified as significant influential factor to reduce farmland fragmentation. Mechanical operations are key determinants of scale management. Compared to farms with high power of agricultural machinery, scatted plots are more vulnerable to fragmentation (Tan et al., 2006). Therefore, farmland ploughed by tractors (PFTr) was positively correlated to AREA_AM and ENND_MN. Effectively irrigated farmlands and those with high yields irrespective of drought or water logging were protected as prime farmlands in practice. They were less influenced by anthropogenic activities, helping slow down the fragmentation process.

Changes of agricultural systems are resulted from multiple drivers as well as their interactions and combinations (Geist and Lambin, 2004). This study demonstrated that different categories of drivers and their combinations exerted different influence on farmland fragmentation. In general, economy was the most influential factor (Table 2). Economic development has close relationship with social activities (e.g., road construction, and real estate investment) and with technological improvement. Consequently, the joint influences between economic and social and cultural drivers, as well as those between economic with scientific and technological drivers accounted for relatively higher proportion in variances (Table 2).

Landscape metrics describe the complex physical patterns in agricultural systems using numerical values. The application of these metrics offers a pathway to investigate the interactions between anthropogenic activity and agricultural systems. More explicitly, the identification of anthropogenic drivers of farmland fragmentation can inform agricultural management in the following aspects: (1) Quantitative prediction of the degree to farmland fragmentation will increase under projected development scenarios in the future will increase for a given region. It can also be retrospectively applied to analyze the changing rate of fragmentation over time for a management unit. (2) It is possible to determine the disruptions from different categories of anthropogenic drivers. Conclusions could be drawn on what was done out of place and what should be done in the future. For example, our results demonstrated that technological factor and education expenses were negative contributors to farmland fragmentation. Managers can therefore mitigate farmland fragmentation through increasing education expenses and improving technology. (3) These principle anthropogenic drivers of farmland fragmentation can be integrated into the existing agricultural management platform or programs, in order to better planning monitoring agricultural systems.

5. Conclusions

This paper focused on farmland fragmentation dynamics in rapidly developing region. Farmland fragmentation presented a linear increasing trend from 1985 to 2013 in Tiaoxi watershed, China. The corresponding demographic drivers included non-agricultural population and migration population, and social drivers included road mileage and investment in real estate. Two groups of economic drivers were identified: one group included fruit and seafood production, another included per capita income and proportion of tertiary industry. Furthermore, the degree of farmland fragmentation would be significantly reduced by technological improvement and education expenses increases. The four categories of drivers exerted different influence on farmland fragmentation. In general, economy was the most influential driver; its joint influences with social and cultural drivers and those with scientific and technological drivers were relatively stronger. The identification of anthropogenic drivers of farmland fragmentation can provide important management implications for better planning monitoring agricultural systems. Further study should investigate the interactions among different anthropogenic drivers, the impacts of anthropogenic activities on farmland fragmentation, and the relative importance of different drivers across time and space. In particular, the interactions between farmland ownership fragmentation and landscape fragmentation and their influences on ecological processes in agricultural systems should to be examined.

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