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Spatial Heterogeneity of Agricultural Science and Technology Parks Technology Diffusion: A Case Study of Yangling ASTP

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Abstract: Agricultural science and technology parks (ASTPs) represent an important growth pole in China's agricultural modernization. Clarifying their diffusion laws can optimize the technological diffusion process and improve its efficiency. Our study uses disaggregated spatial information in its model to analyze ASTP technology diffusion in a heterogeneous space. We constructed a comprehensive index system to evaluate the diffusion environmental quality and introduced the heterogeneous diffusion equation to calculate the technological diffusion probability. We applied this framework to a real-world scenario: the apple planting technology diffusion of the Yangling ASTP in the Loess Plateau, China. The results indicated: 1) the technological diffusion environment of the Loess Plateau advantageous apple producing area showed strong spatial heterogeneity caused by climate, topography, and external transportation links. 2) Under the combined effects of distance and spatial heterogeneity, the spatial diffusion pattern of the Yangling ASTP apple technology was expansion diffusion supplemented by hierarchical diffusion and banded diffusion, and 3) ASTP technology diffusion showed a strong distance attenuation effect, and the frictional effect of distance can be decreased by improving the diffusion environmental quality. These laws can promote regional balanced ASTP-driven development.

Keywords: agricultural science and technology park (ASTP); heterogeneous environments; diffusion environment; diffusion probability; heterogeneous space diffusion equation

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1 Introduction

Science and technology parks (STPs), in their many different forms, now exist worldwide, and they are considered a proven policy tool spurring economic growth and enhancing technological competitiveness (Hobbs et al., 2017). As a type of STP, agricultural science and technology parks (ASTPs) are the transformation models of new agricultural science and technology (AST), which emerged in China during the agricultural modernization process of the 1990s (CRTDC, 2017). ASTPs encourage high-tech companies to collaborate, and they promote favorable policies such as tax holidays (Hu, 2007). The objective of ASTPs is to expedite the adoption of new agricultural technologies through geographically localized knowledge spillover (Ribeiro et al., 2016). Currently, there are more than 5000 national, provincial, and prefecture-level ASTPs in China. By the end of 2017, the 246 national ASTPs covered an area of 3860 km^2 and a demonstration area of 133 333 km^2 (ht-

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tp://www.most.gov.cn/xxgk/xinxifenlei/fdzdgknr/fgzc/gfxwj/gfxwj2018/201801/t20180130_137945.html). After more than 20 yr of development ASTP has become an important technology growth pole in the process of agricultural modernization in China (CRTDC, 2017).

Existing studies have focused more on the development of STPs (Shin, 2001) and less on the interaction between them and regional development. Most works examine the relationships between entities in an STP (Latorre et al., 2017), such as the interaction and networking between STPs and universities (Good et al., 2019). A few have analyzed obstacles that hamper STPs' success (Dhewanto et al., 2016) and identified strategies to make them successful (Guadix et al., 2016). However, as a technology zone or technical pole for agricultural development and areas in China, ASTPs must sustain their development while promoting regional development through the transfer of AST achievements (Li and Luo, 2016). Moreover, agricultural production is characterized by heavy dependence on land and limited mobility. This makes ASTP technology diffusion particularly challenging. Therefore, we believe it necessary to fully understand the technological diffusion laws of ASTPs to optimize their technology diffusion process and improve their efficiency.

Diffusion is a fundamental process that manifests itself in various physical, biological, social, and economic contexts. Rogers and Shoemaker (1971) defined innovation diffusion as the process by which an innovation spreads among members of a social system. This process involves the innovation, its adopters, its channels, time and space, and heterogeneous cultures and economies. The results of economic geography and rural sociology studies indicate considerable spatial variation in technology diffusion (Redmond, 2003). That is, diffusion rates in technology diffusion are context-specific, depending on factors such as socioeconomic acceptance, technological advances, and institutions that promote or impede diffusion (Narayan, 2001). The effect of environmental heterogeneity on the diffusion of agricultural technologies has been extensively documented, as Diamond (1999) noted that agricultural technologies spread more slowly in regions with large geographical differences. Assunção et al. (2019) combined nuanced geographic data with information on direct cropping system dispersion in Brazil to demonstrate that increased geographic heterogeneity is associated with lower technology adoption, which validates Diamond's assertion. Steffens (1998) showed that diffusion patterns of agricultural technologies vary by geographic region and considering these regional differences can improve short- and long-term technology diffusion predictions under certain conditions. Allaire et al. (2015) found that spatial heterogeneity in the spread of organic agriculture in France was due to regional differences in the ability to absorb and convert organic agriculture (a combination of natural, socioeconomic, and political factors). Kuo and Peters (2017) showed that regional differences in the spread of organic agriculture were closely related to heterogeneity in ecological factors such as climate and topography. Beretta et al. (2018) demonstrated the importance of cultural heterogeneity to understand the technology diffusion process in five Ethiopian villages. Thus, it is necessary to study the influence of environmental heterogeneity on agricultural technology diffusion. Focusing on a heterogeneous environment's influence on ASTP technology diffusion can effectively reveal the laws of technology diffusion in ASTPs.

Heterogeneity had also been extensively examined. The micro-modeling approach used by Chatterjee and Eliashber (1990) developed a model of the innovation diffusion process that explicitly considered individual-level determinants of adoption and allowed for heterogeneity in these determinants. Strang and Tuma (1993) developed individual-level diffusion models that incorporated spatial and temporal heterogeneity within an event-history framework. These models can be estimated from event-history data by the adoption times from individuals. Young (2009) incorporated heterogeneity into three broad classes of models—contagion, social influence, and social learning. Chatterjee and Xu (2004) built a social learning model based on the random walk model. The important role of imitation in technology diffusion was verified by assuming that the probability of individual technology adoption depends on the outcomes and technology choices of observable neighbors as well as their outcomes. Leite and Teixeira (2012) followed the tradition of evolutionary models of technological change, and put forward a computational diffusion model with heterogeneous agents. Their model emphasized social interactions between agents who were heterogeneous in managing networks.

Although the above model considers the impact of heterogeneity on technology diffusion, it focuses more on individual-level heterogeneity and ignores environmental heterogeneity. The Heterogeneous Spatial Diffusion Model (HSDM) proposed by Shan and Bao (1995) converts the motion of a technology on a two-dimensional plane into a three-dimensional stochastic motion along the plane and in the direction of the integrated quality of the local natural, social, and economic environment by adding the integrated quality dimension of the diffusion environment. It effectively reflects the influence of the heterogeneity of the diffusion environment on the diffusion process. Therefore, the application of HSDM to ASTP technology diffusion can more objectively reveal the ASTP technology diffusion pattern under heterogeneous environments.

One of the challenging problems in applying HSDM to ASTP technology diffusion research involves the estimation of HSDM parameters, e.g., the quality of the diffusion environment needs to be measured according to different technology types. We proposed a framework for analyzing the diffusion patterns of ASTP in heterogeneous environments and applied it to a real-world scenario: apple cultivation technology diffusion from the Yangling ASTP in the Loess Plateau, China. We first constructed an index system for evaluating the environmental quality of apple cultivation technology diffusion in the study area by summarizing the factors influencing its diffusion. Second, we determined the HSDM parameters based on the sampling survey of the study area. Finally, the HSDM was used to calculate the diffusion probability of the Yangling ASTP apple cultivation technology with each unit in the study area. As will be demonstrated, our approach can effectively use dispersed spatial information to predict the diffusion probability from diffusion sources to different regions. Moreover, our study can clarify what determines the diffusion environment's heterogeneity and how it affects the technology diffusion process. The purpose of this study is to reveal the technological diffusion laws of ASTPs in heterogeneous environments using a rational and effective method, thus providing insights for designing effective technology promotion strategies.

2 Data and Methods

2.1 Study area

This study takes Yangling ASTP as a subject for empirical research and focuses on the apple-planting technology diffusion of Yangling ASTP in the Loess Plateau apple advantageous production area, China. Yangling ASTP was established in 1997 and belongs to Shaanxi Province of China (107°59′E–108°08′E, 34°14′N–34°20′N) with a planned area of 22.12 km^2 (Fig. 1). Yangling ASTP has a substantial advantage in R&D and the introduction, and promotion of apple cultivation technology. In terms of the introduction and breeding of new apple varieties, the introduced Pink Lady and Pink Lady varieties are characteristic of the late ripening crops in Shaanxi Province. The cultivation efficiency of the

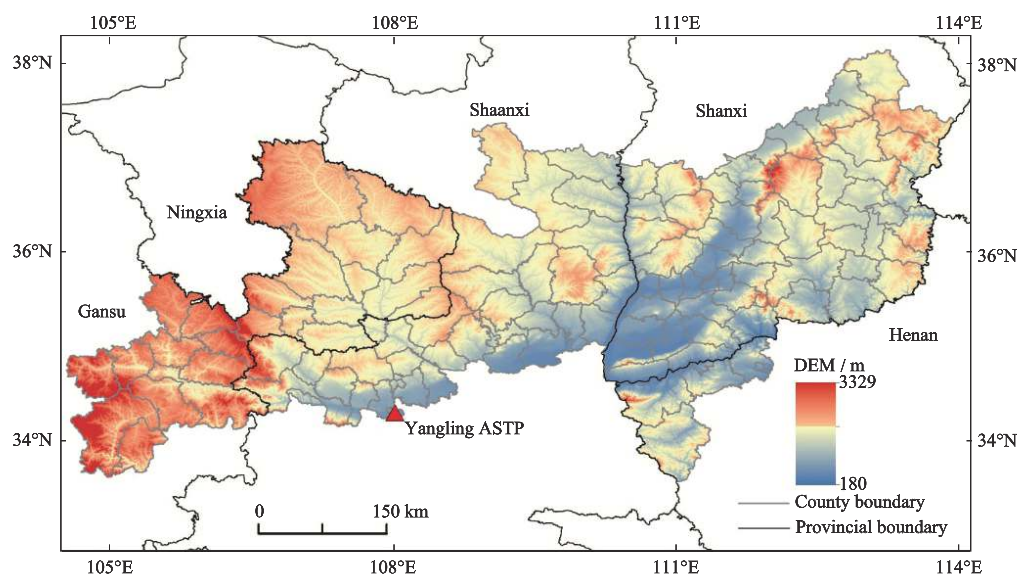

Fig. 1 Regional map of the Loess Plateau apple advantageous production area and location of the Yangling agricultural science and technology park (ASTP)

Ruiyang and Ruixue varieties is two to three times higher than the main traditional Fuji variety. The Ruiyang and Ruixue varieties are alternative species to the existing apple cultivars in the Loess Plateau.

From the perspective of technology promotion, the Yangling ASTP focuses on demonstration park construction, and promoting advanced and practical key technologies such as green fruit base construction, orchard grass growing, hole storage fertilizer and water, and dryland dwarf apple cultivation. A series of mature and effective technology promotion models were formed. The promotion models include university science and technology demonstration, industry chain enterprise, science and technology commissioner entrepreneurship, agricultural science and technology training, media science and technology demonstration, and agricultural exhibition. The sustainable intensive apple cultivation model's demonstration and promotion have been widely applied in the main apple production areas of Weibei in Shaanxi and Longdong in Gansu. It is effectively promoting the technological progress of the apple industry in the Loess Plateau. The Yangling ASTP has become the core source of in the Loess Plateau and has a strong radiation-driven effect on apple industry development.

The Loess Plateau advantageous producing area is the major apple-producing area with the largest cultivated area and highest apple yield in China (DSTEMARA, 2018) (Fig. 1). The main goal of its construction was to radiate the development of the agricultural industry in arid and semi-arid regions (SC, 2018). The Loess Plateau advantageous production area is located in the arid and semi-arid regions, therefore, it is also the main diffusion area of the Yangling ASTP apple technology.

2.2 Evaluation of diffusion environmental quality

2.2.1 Selection of indicators

Because producers decide to adopt specific agricultural practices within a range of social, economic, environmental, and agronomic constraints. Therefore, the technology diffusion environment of ASTPs is complex and involves many external factors that affect the diffusion process (Li and Luo, 2016). The diffusion environment affects the spatial flow direction, speed, method, and effect of technology diffusion as well as the entire technology diffusion process (Ormrod, 1990; Wejnert, 2002). Also, the environment determines the economic and infrastructure conditions necessary for technology diffusion (Nelson, 1995). Through comprehensive analysis of various factors affecting ASTP technology diffusion, we constructed an evaluation index system considering five aspects: natural settings, the level of agricultural development, agricultural policy conditions, societal culture, and the information network environment. Each aspect involves several reference indicators (Table 1).

(1) Natural settings. Agriculture is highly dependent on natural factors. Different natural environments determine different agricultural production methods as well as different agricultural technology needs. Climate change has a significant impact on agricultural productivity (Eitzinger et al., 2010). Topography affects the spatial pattern of land use (Geng et al., 2019) and soil moisture distribution (Raduła et al., 2018) and affects the growth and production of vegetation and major crops (Muñoz et al. 2014). Muthoni et al. (2017) used slope and soil conditions as important factors in measuring natural environmental conditions when delineating the potential recommended domains for agricultural technologies. Noltze et al. (2012) demonstrated that slope and soil conditions have strong explanatory power for understanding farmers' technology adoption decision processes. Therefore, we evaluate the natural environmental conditions that influence technology diffusion in terms of climate, topography, and soil conditions.

(2) Agricultural development levels. An objective assessment of the agricultural development levels in a region clarifies the direction and type of agricultural technology diffusion. Water conservancy facilities are important factors in agricultural production and play a vital role in improving agricultural production conditions (Zhang, 2009). Infrastructure development is highly correlated with the level of economic development (Deller, 2001). Scale management of agriculture is the only way to realize agricultural mechanization. The use of mechanical technology increases agricultural productivity and reduces unit costs of crop production (Pingali, 2007). The higher the land output, the higher the enthusiasm among agricultural operators for the adoption of new technologies. We use water conservancy facilities, the degree of agricultural mechanization, the level of economic development, the level of large-scale agriculture, and the efficiency of land output to evaluate the level of agricultural modernization in the region.

(3) Agricultural policy. Tax incentives or policies for new agricultural technologies play an obvious role in

Table 1 The quality evaluation indicators of apple planting technology diffusion environment

Target layers	Rule layers	Weights	Index layers
Natural settings	Climatic conditions	0.1323	Annual average temperature
			Annual precipitation
			The temperature in mid Jan.
			The extreme lowest temperature in a year
			The average temperature in summe
			The average lowest temperature in summer
			The days over 35℃ in a year
	Terrain conditions	0.0625	Slope
	Soil conditions	0.0653	Soil types
Agricultural developmental levels	Water conservancy facilities	0.0875	The irrigation rate of arable land / %
	The degree of agricultural mechanization	0.0484	The diesel consumption per hectare arable land / (t/ha)
	The level of economic development	0.0449	The capita disposable income of rural residents / (yuan (RMB)/(capita·yr))
	The level of large-scale agriculture	0.0809	The proportion of scale agricultural operators in agricultural operators / %
	The efficiency of land output	0.0470	The crop yield per hectare arable land / (kg/ha)
Agricultural policy conditions	The support of agricultural policy	0.0589	The proportion of agricultural financial expenditure to public financial expenditure / %
	Labor scale	0.0816	The number of agricultural labor per hectare arable land / (capita/ha)
Societal cultures	The quality of agricultural labor force	0.0508	The proportion of agricultural labor with high school education or above / %
	The development of intermediary agencies	0.0557	The proportion of agricultural labor aged 35 and below / %
Information network environments	The convenience degree of traffic	0.0945	The number of agricultural business agencies
	The level of communication facilities	0.0555	The density of external roads
		0.0342	The proportion of villages with broadband Internet / %

supporting the diffusion of agricultural technologies. Intervention in credit markets and investment in infrastructure can have a positive impact on the adoption process (Carauta et al., 2017). Therefore, we use agricultural policy support as the main criterion for measuring the agricultural policy environment.

(4) Societal cultures. The acceptance of new technologies is closely related to the age structure of local people (Sarker et al., 2020), education levels (Drewry et al., 2019), cultural background, and preferences in the region. Those with a higher education tend to be the pioneers of new technologies while those with a lower education tend to be followers (Mignouna et al., 2011). The cultural quality of the adopters determines their level of technology mastery and their proficiency in the use of technology. Regarding age composition, the majority of young people tend to gravitate toward high-risk, high-paying technologies while the elderly tend to prefer mechanized technologies that reduce labor intensity (Barrera et al., 2005). Therefore, we evaluate the regional social and cultural environment considering the two aspects of labor scale and labor quality.

(5) Information network environment. The availability of information positively impacts technology needs (Wyche and Steinfield, 2015). To begin with, information may shape problem awareness and attitudes, which have been shown to be important factors in framing the outlooks and expectations of farmers regarding technology choice (Lee, 2005; Campenhout, 2019). Second, more information can increase the imitation behavior of potential adopters (Feder and Umali, 1993). Proper communication infrastructure can reduce the cost of in-

formation dissemination. Therefore, we selected three indicators: intermediary service status, transportation convenience, and the level of information infrastructure to evaluate the regional information network environment.

2.2.2 Measurement of the diffusion environmental quality

To fully consider the influence of external environmental factors on the technology diffusion probability of ASTP, we combine the subjective weighting method (AHP) (Ramanathan, 2006) and the objective weighting method (Delphi method) (Khorramshahgol and Moustakis, 1988) to determine the weight of each specific index, and we establish the evaluation model for the technology diffusion environment of ASTPs by weighted sum. It can be expressed as:

$$m = \sum_{i=1}^{n} P_i X_i \quad (i = 1, 2, \ldots, n) \tag{1}$$

where m is the quality index of technology diffusion; P_i is the weight coefficient of the ith indicator X_i; and n is the total number of evaluation indexes.

2.2.3 Spatial analysis of diffusion environmental quality

The semivariogram is a continuous function used to describe the spatial continuous variation of a regionalized variable, which reflects the change in a regionalized variable between the observed values at different distances. This study used the variogram to investigate the spatial variability of the quality of technology diffusion environment in the study area. The semivariance $\gamma(h)$ is defined as (Miranga et al., 1992):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (Z_i - Z_{i+h})^2 \tag{2}$$

where Z_i is sample value at point i, Z_{i+h} is the value of the dependent variable at a point separated from point i by distance h, and $N(h)$ is the number of pairs of points separated by distance h. The semivariogram is the plot of $\gamma(h)$ as a function of h.

2.3 HSDM applications for ASTP technology diffusion

In a homogeneous space, technology diffusion is only related to distance, which makes technology continuously diffuse outward from the source with the same diffusion trend. For technology diffusion of ASTPs, the heterogeneity of diffusion space makes technology diffusion disperse in the form of non-equivalent and non-equilibrium at the macro level. The concept of field pixels, which first appeared in the geography field as the geographical diffusion theory, is the smallest functional spatial unit under geographical observation (Bossler et al., 2002). In this paper, the smallest spatial unit discussed in ASTP technology diffusion is defined as 'diffusion field pixels'. The geographical conditions, resource endowments, infrastructure conditions, technological economic environment, and human environment within a single field pixel are similar. Different field pixels constitute a heterogeneous diffusion space (Fig. 2). The diffusion environmental quality is measured by the results of a comprehensive evaluation of natural environmental, socio-economic, and cultural factors within the diffusion field pixels, which represents the ability of an individual diffusion field pixel to absorb innovative technologies. The technology diffusion probability of ASTPs to each diffusion field pixel is influenced by the diffusion environmental quality and the distance between the ASTP and diffusion field pixels. The HSDM proposed by Shan and Bao (1995) can effectively reflect the technology diffusion process under the combined effect of diffusion environmental quality and distance. In other words, this approach can represent the influence of heterogeneous environments of technology diffusion. It can be calculated as:

$$D(x,m) = D_{\max} \times F(x,m) = D_{\max} \times erfc\left(\frac{x}{\sqrt{4Z(m)}}\right) \qquad x \geqslant 0 \tag{3}$$

where $D(x, m)$ is the diffusion probability; $D_{\max}$ is the maximum diffusion probability; $erfc(x)$ is the Gaussian confutation; $Z(m)$ is the diffusion coefficient function; x is the standard distance from the diffusion field pixels to the diffusion source; and m is the diffusion environmental quality of the diffusion field pixels.

There are two key subfunctions in Equation (2), the Gaussian confutation $erfc(x)$, and the diffusion coefficient function $Z(m)$. There is no uniform equation for $Z(m)$ because it must be determined by trial calculation according to the trend relationship among the diffusion environmental quality, distance, and technology diffusion probability under the condition of a strictly controlled residual. Therefore, determining the parameters of HSDM for ASTP technology diffusion is as follows:

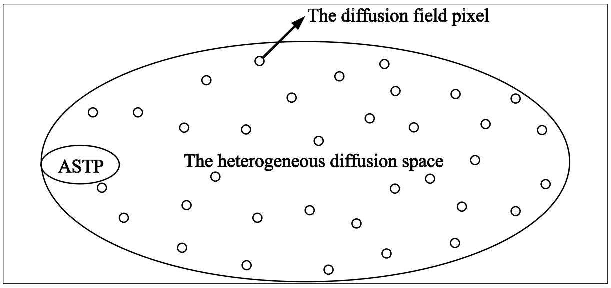

Fig. 2 A schematic showing the technology diffusion system of ASTPs in heterogeneous space

first, using Equation (1) calculate the diffusion environmental quality, while calculating the standard distance from the diffusion field pixels to the ASTP; second, make a uniform selection of the appropriate number of sample points in the study area, and perform a trend analysis of the sample points x, m and diffusion probability $D(x,m)$, and determine the specific expression for $Z(m)$; third, determine the boundary, that is, the maximum and minimum values of the diffusion probability are determined respectively. The relationship between the Gaussian confutation $erfc(x)$ and the normal distribution function $\Phi(x)$ is used to solve $erfc(x)$, and the diffusion probability's maximum and minimum values, and minimum values corresponding to the diffusion environmental quality m and the standard distance x are substituted into the HSDM to determine the specific expression of $Z(m)$ parameter A, to determine the measurement equation of the technology diffusion probability of the ASTP in a heterogeneous environment.

2.3.1 Z(m) specific expression determination

In the empirical study, we take the county-level unit represent the diffusion field pixel. Six counties were evenly selected as sample sites in the Loess Plateau apple advantageous production area, with the Yangling ASTP as the center (Fig. 3). The technology diffusion probability from the Yangling ASTP to the sample sites is measured in terms of macro-policy linkages and the dissemination of sustainable intensive apple cultivation models. The macro-policy linkage here measures the degree of technology linkage between the apple technology extension agents in the sample sites and the Yangling ASTP, while the dissemination of the sustainable intensive cultivation model measures the implementation of Yangling ASTP apple cultivation technology after its introduction. Due to the general nature of the technologies promoted by the Yangling ASTP such as conformal pruning, integrated pest management, and orchard grassing, it is difficult to define the source of these technologies as exclusively Yangling ASTP, so we do not consider them when measuring the technology implementation.

The macro-policy linkages were evaluated by taking six questions from the six main technology promotion models for the apple in the Yangling ASTP described above (Table 2). The macroscopic promotion of the sustainable intensive cultivation model was evaluated using its proportion of the county's apple cultivation area, and the implementation of the technologies on the ground was evaluated using six questions based on the key technologies of the sustainable intensive cultivation model (Han, 2009) (Table 2). The weights of the 12 questions were determined by interviewing eight apple technologists from four apple experiment demonstration stations in Baishui, Qianyang, Luochuan and Qingcheng, Yangling ASTP, and using the subjective and objective weighting methods of AHP and entropy method (Table 2). Finally, we used the survey data of six sample counties to determine the diffusion probabilities of Yangling ASTP's apple cultivation technology in the six sample counties through a weighted summation method.

For the six sample counties, trend analysis was performed on three sets of data: the technology diffusion probability, the diffusion environmental quality m (calculated from the technology diffusion environmental quality measurement model above), and the standard distance x from the Yangling ASTP (Table 3).

$$Z(m) = Am^2 \tag{4}$$

where A is the coefficient to be determined.

2.3.2 Determination of parameters A

(1) Determination of boundary conditions. The Yangling district, where the Yangling ASTP is located,

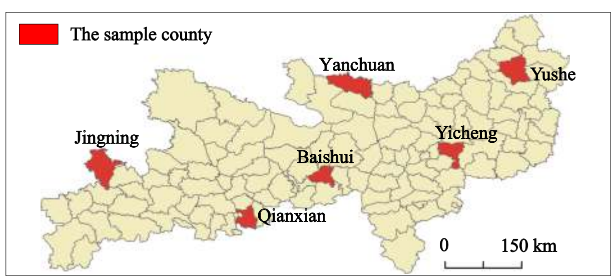

Fig. 3 Spatial distribution of sample counties in the Loess Plateau apple advantageous production area

Table 2 Definitions and summary statistics of the variables used in the evaluation of diffusion probabilities in the sample counties in the Loess Plateau, China

Variables	Descriptions		Weights
Macro-policy Linkages	Does Yangling ASTP have a pilot demonstration station in your county? (Yes=1, No=0)		0.1015
	Is there a technical connection to a demonstration station near your county? (Yes=1, No=0)		0.0808
	Is there Yangling ASTP technical experts in the apple extension system in your county? (Yes=1, No=0)		0.0912
	Does your county regularly send apple extension workers to Yangling ASTP for training? (Yes=1, No=0)		0.0802
	Does your county invite Yangling ASTP apple technical experts to do technical training in your county? (Yes=1, No=0)		0.0769
	Is your county participating in the Yangling Agricultural High-Tech Achievement Fair? (Yes=1, No=0)		0.0511
Implementation of sustainable intensification models	Promotion Scale	Sustainable intensive acreage as a percentage of total county apple acreage / %	0.0897
	Farmers'mastery of sustainable intensification technologies	How many years of trees are appropriate for Sustainable Intensive Cultivation Models? (Correct=1, Wrong=0)	0.0546
		What is the height of the rootstock above the ground in dry and watered ground at planting time? (Correct=1, Wrong=0)	0.0614
		How many meters between rows and plants are controlled when planting? (Correct=1, Wrong=0)	0.0734
		What is a reasonable control range for tree height and canopy radius, respectively? (Correct=1, Wrong = 0)	0.0856
		What shape should be controlled for the apple tree? (Correct=1, Wrong=0)	0.0627
		What is the most effective way to apply organic fertilizer? (Correct=1, Wrong=0)	0.0909

Table 3 Technology diffusion probability, diffusion environmental quality and standard distance of six sample counties in the Loess Plateau, China

Measurement indicators	Qianxian	Jingning	Baishui	Yanchuan	Yicheng	Yushe
Standard distance	0.052	0.411	0.289	0.563	0.620	0.919
Diffusion environmental quality	0.284	0.296	0.389	0.244	0.397	0.298
Technology diffusion probability	0.896	0.318	0.592	0.097	0.261	0.027

is zero distance from the diffusion source and has the largest diffusion environmental quality among 121 counties (cities), so we believe that the Yangling ASTP has the largest diffusion probability value for the Yangling district; that is $D_{\max} = 1.0$. In the process of determining the boundary condition of minimum dispersion probability, we selected the five counties with the largest distance from Yangling ASTP from all counties (cities) in the study area, namely Yushe, Yuzhi, Zuoquan, Heshun, and Shouyang. Yushe had the lowest diffusion environmental quality (the diffusion environmental quality in Yushe, Yuzhi, Zuoquan, Heshun, and Shouyang counties was 0.298, 0.362, 0.399, 0.375, and 0.342, respectively). Furthermore, through telephone interviews with their agricultural departments, we learned that four: Yuzhi, Zuoquan, Heshun, and Shouyang prioritized the development of the apple industry, but only Beizhai Township in Yushe County has a tradition of apple cultivation, which they transformed into a high-quality dried walnut economic forest. Based on the interview results and considering the distance and diffusion environmental quality, we concluded that the Yangling ASTP has the lowest diffusion probability for Yushe among all counties (cities) in the study area. Based on the above calculation results, we can see that the probability of diffusion in Yushe County is 0.027.

(2) Calculation of parameter A. Since the Gaussian cofunction and the normal distribution function have the following relationship:

$$erfc(x) = 2 - 2\Phi\left(\sqrt{2}x\right) \quad (5)$$

we obtain the numerical calculation of $erfc(x)$ by the numerical calculation of $\Phi\left(\sqrt{2}x\right)$.

The approximate calculation formula for the normal distribution is:

$$\Phi(x) = 1 - \frac{1}{2}\left(1 + \sum_{i=1}^{4} a_i x^i\right)^{-4} \quad (6)$$

where a_1 = 0.196 854, a_2 = 0.115 194, a_3 = 0.000 344, a_4 = 0.019 527 (Hastings et al., 1995).

The maximum diffusion probability, minimum diffusion probability determined in the previous boundary condition determination section and their corresponding diffusion environmental qualities and distances, as well as the approximate formula for *erfc* (x) determined above, are substituted into HSDM to determine the parameter A = 0.967 152 087 4. Substituting A into equation (1), the probability equation for the technology in the study area is obtained as:

$$D(x,m) = D_{\max} \times erfc\left(\frac{x}{\sqrt{4Am^2}}\right) = erfc\left(\frac{x}{\sqrt{3.8\,686\,083\,495\ m^2}}\right) \tag{7}$$

With this equation, we calculated the technology diffusion probability of ASTPs for each apple plantation base county.

2.4 Data source and processing

The geographical data used in this study include: 1) digital elevation model (DEM) data with a resolution of 30 m, which was obtained from the geospatial data cloud (http://www.gscloud.cn/). 2) Temperature and precipitation data from meteorological stations within the 121 apple plantation counties and 228 surrounding stations for 10 consecutive years from 2009 to 2018. These data were derived from the Chinese Academy of Sciences Resource and Environment Data Cloud Platform (http://www.resdc.cn). 3) External traffic density map from the National Geographic Information Resource Catalog Service System (http://www.webmap.cn). We obtained data on the length of roads at the provincial level and above for each apple-planting base and calculated the external traffic density based on the area of each base county. 4) Soil type data from the National Tibetan Plateau Data Center (http://westdc.westgis.ac.cn).

Additionally, socio-economic data were required for our study. These data include: 1) statistics from the statistical yearbooks of each county within the study area including the irrigation rate of arable land, diesel consumption per hectare of arable land, per capita disposable income of rural residents, crop yield per hectare of arable land, and the proportion of agricultural financial expenditure to public financial expenditure. 2) The proportion of scale agricultural operators among agricultural operators, the number of agricultural laborers per hectare of arable land, the proportion of agricultural labor with a high school education or above, the proportion of agricultural labor aged 35 and below, the proportion of agricultural business agencies, and the data for broadband Internet villages are from the main data bulletin of the third national agricultural census of each county. 3) The lists of new business entities, such as leading enterprises, family farms, and cooperatives in each county of the research area, are from China Customer Network (http://www.ltmic.com/index).

Macro-policy linkages and areas of sustainable intensive cultivation patterns in sample counties were obtained through in-depth interviews with the heads of fruit management departments and horticultural station fruit tree specialists in the sample counties. We designed questionnaires based on the questions proposed in Table 2 about the mastery of sustainable intensification techniques, and randomly selected 20 apple growers in each of the six sample counties from July to September 2019, and conducted questionnaire surveys on the implementation of sustainable intensification cropping patterns in each sample county. We completed 120 questionnaires, excluding 3 invalid questionnaires with incomplete information and obvious errors in logic, and finally obtained 117 valid questionnaires, with a valid return rate of 97.5%.

3 Results and Analysis

3.1 Spatial distribution characteristics of technology diffusion environments

We used the multi-factor weighted method to calculate the comprehensive score for the quality of technology diffusion environments in each county of the study area. To show the overall environmental differences in the main apple-producing areas of the Loess Plateau, we used the natural breakpoint method in ArcGIS to divide the quality of the technology diffusion environments into five classes: the highest level, the high level, the medium level, the relatively lower level, and the lowest level, as shown in Fig. 4. Among the 121 counties, the proportions of the five classes are 2.50%, 25.00%, 35.00%, 23.33%, and 14.17%. The proportion of counties with high quality technology diffusion environments in the study area was 27.50% while the highest level counties accounted for only 2.50%. However, the proportion of middle and below levels was as high as 72.47%. Overall, the level of technology diffusion environments in the study area is not high, and there are particularly few counties with high-level technology diffusion environments.

The value of the technology diffusion environmental quality of each county is assigned to the geometric center point of the corresponding county, and we generate a spatial data set. Since the average closest distance between counties in the study area is 40.50 km, the sampling step is thus set as 41.00 km. We calculate the experimental variograms on this basis. The sample data were fitted using a sphere model, Gaussian model, exponential model, linear model, and other models. The semivariance results of the fitted model are shown in Table 4. Based on the principle of minimum residuals *RRS* and maximum determination coefficients R^2, the variation function that determines the quality of the technology diffusion environment conforms to the index model. The nugget value (C_0) stands for the discontinuous variation of the technology diffusion environmental quality at small scales and the abutment value (C_0+C) reflects the maximum variation when the technology diffusion environmental quality varies from small to large with distance. The ratio of nugget value to abutment value $C_0/(C_0+C)$ is the proportion of the random part of the total spatial variation, which is inversely proportional to the proportion of the spatial autocorrelation part, which can be used as a classification basis for the spatial autocorrelation of research factors. The ratio $C_0/(C_0+C)$ of the fast gold value to the abutment value of the technology diffusion environmental quality in the case area was 16.60%, indicating that approximately 16.60% of the total spatial variation of the technology diffusion environment was caused by random factors below the county, and the spatial variation caused by the autocorrelation part accounts for 85.77%. Obviously, the environmental quality of technology diffusion in the case area shows a strong spatial

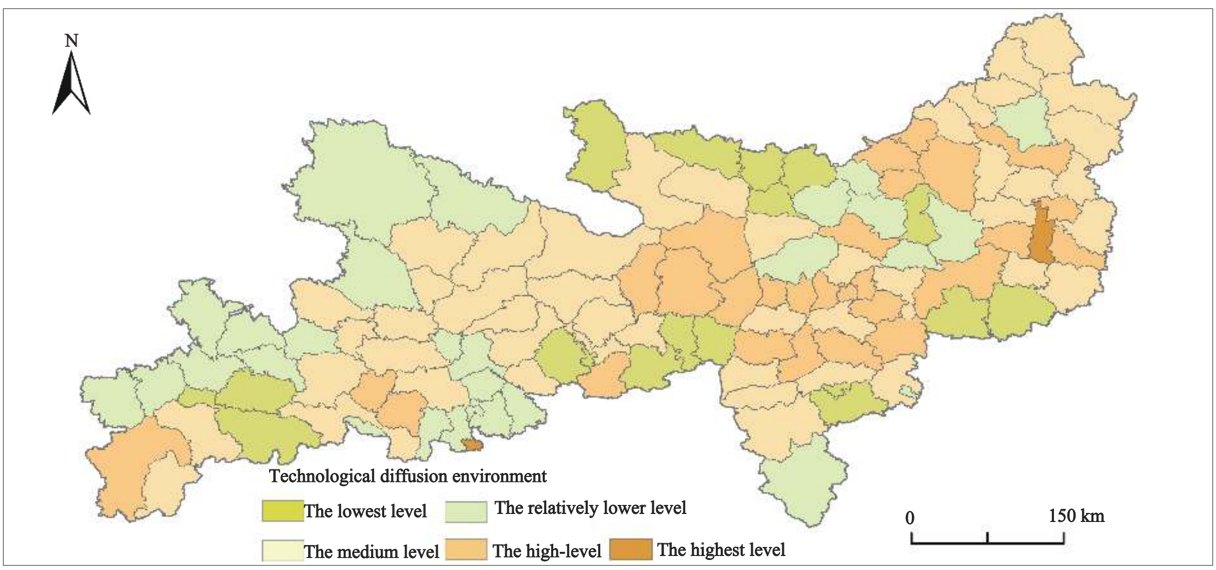

Fig. 4 Distribution of diffusion environmental quality in the Loess Plateau apple advantageous production area, China

Table 4 Semivariogram models and parameters of technology diffusion environment

Models	C_0	C_0+C	$C_0/(C_0+C)$	a	R^2	*RSS*
Exponential model	0.011	0.065	0.166	138.00	0.871	0.00010
Spherical model	0.033	0.065	0.499	188.00	0.869	0.00011
Gaussian model	0.033	0.065	0.499	129.90	0.855	0.00012
Linear model	0.053	0.069	0.776	509.04	0.347	0.00051

Notes: a stands for the spatial autocorrelation range of the technology diffusion environmental quality. R^2 is the determination coefficient, and the larger the R^2, the better the model fit. *RSS* is the residual sums of squares, and the smaller the *RSS*, the better the model fit. C_0 is nugget value; (C_0+C) is abutment value autocorrelation. The spatial structure is strongly influenced by structural factors such as climate, terrain, external traffic conditions beyond the county area, policy environment, and the social and cultural environment. The influence of factors within the county unit on the spatial structure of technology diffusion environment is not significant. The magnitude of the range reflects the scale of spatial heterogeneity. The spatial autocorrelation range of the technology diffusion environment is 138.00 km, indicating that the influence of various structural factors is mainly concentrated within 138.00 km. The anisotropy ratio describes the anisotropic structural characteristics of the technology diffusion environment. The anisotropy ratio describes the anisotropic structural characteristics of the technology diffusion environment. The anisotropy ratio in the four directions of the technology diffusion environment is equal to 1, indicating that the spatial heterogeneity of the technology diffusion environment is isotropic.

3.2 Measurement of the technology diffusion probability

Based on the distance of 121 counties from Yangling ASTP and the quality of the technology diffusion environments, according to Equation (7), we calculated the technology diffusion probability in each county using Matlab. We used the natural breakpoint method to divide the technology adoption probability into five levels: the highest level, the high level, the medium level, the relatively lower level, and the lowest level (Fig. 5). Overall, with the increase in the distance between the counties to the Yangling ASTP, the technology diffusion probability shows a continuous decreasing trend in space. At the local level, the technology overcame the limitation of distance and diffused preferentially to some counties (cities) with high quality diffusion environment, which showed obvious jump in space. As shown in Fig. 5, Yangling ASTP apple cultivation technology has jumped and diffused in Fuping County, Linyi County and Changzhi County. In addition, the technology diffused along the main traffic arteries, forming three diffusion zones along the Beijing-Kunming Expressway, Hohhot-Beihai Expressway and Lingchuan-Houma Expressway. In summary, the Yangling ASTP apple cultivation technology showed a spatial diffusion pattern mainly based on expansion diffusion, supplemented by zonal diffusion and hierarchical diffusion.

3.3 Relationships between the diffusion probability and the diffusion environmental quality

We analyzed the relationship between the diffusion probability and the standard distance and found that distance determines the overall diffusion trend of Yangling ASTP. For example, the diffusion environmental quality in Wangyi District and Daning County is 0.250 and 0.251, the standard distance is 0.207 and 0.557, and the

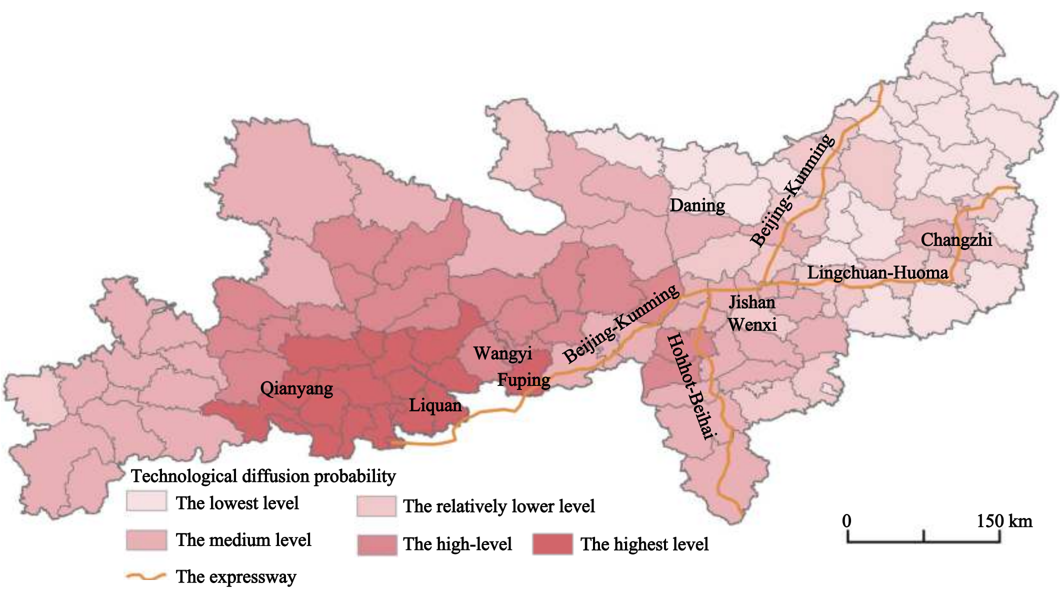

Fig. 5 Spatial distribution of technology diffusion probability of Yangling agricultural science and technology park (ASTP) in the Loess Plateau apple advantageous production area

technology diffusion probability is 0.552 and 0.111, respectively. Although the diffusion environmental quality in both Wangyi District and Daning County is relatively low, the distance between Wangyi District and Yangling ASTP is much smaller than that of Daning County, resulting in a technical diffusion probability in Wangyi District that is nearly five times that of Daning County. In Qianyang and Jishan, the diffusion environmental quality is 0.455, the standard distance is 0.157 and 0.496, and the technical diffusion probability is 0.804 and 0.434, respectively. Although the diffusion environmental quality is equally high in both counties, the distance between Jishan and the Yangling ASTP is much greater in Jishan than in Qianyang, making the probability of dispersion in Jishan much lower than in Qianyang.

The relationship between diffusion probability and diffusion environment of each county (city) in the study area was analyzed. We found that the spatial match between diffusion environment and diffusion probability in Yangling ASTP technology diffusion was low, that is, counties (cities) with low diffusion environment had high diffusion probability because they were close to Yangling ASTP, while counties (cities) with high diffusion environment had low diffusion probability because they were far away from Yangling ASTP. For example, in Wenxi and Liquan counties, the natural conditions, agricultural development level, agricultural policy environment, social and cultural environment, and information network environment of Wenxi County were better than that of Liquan County. However, because the distance of Liquan County from Yangling ASTP (0.086) was much smaller than that of Wenxi County (0.526), the dispersion probability of Liquan County (0.828) was much larger than that of Wenxi County (0.266).

To further reveal the relationship between technology diffusion probability, diffusion environment and distance, we constructed a 3D grid surface diagram of 'technology diffusion probability—standard distance from diffusion field pixels to the ASTP—diffusion environmental quality' constructed based on results of Equation (5) (Fig. 6). From the perspective of the overall trend, the technology diffusion probability obeys the traditional law of increasing with improvements in the diffusion environmental quality and decreasing with an increase in the distance from ASTPs. Specifically, when the distance from the ASTP is fixed, the higher the diffusion environmental quality of the diffusion field pixel, the higher the technology diffusion probability. Similarly, when the diffusion environmental quality of the diffusion field pixels is the same, the closer the diffusion field pixel is to the park and the higher the technology diffusion probability. In general, the higher the environmental quality of the diffusion field pixel and the closer it is to the ASTP, the greater the technology diffusion probability.

We take section lines with normalized diffusion environment values of 0.2, 0.4, 0.6, and 0.8, from Fig. 6, and the result is shown in Fig. 7. From Fig. 7, we see that the scattered points of the diffusion field pixels fall roughly between $m = 0.2$ and $m = 0.8$, and the overall technology diffusion probability decreases with the increasing distance. However, due to the spatial heterogeneity of the technology diffusion environments, under different technology diffusion environmental quality levels, the trend of technology diffusion probability with distance differentiates significantly. The probability of technical diffusion shows a significant distance attenuation effect. Specifically, the higher the diffusion environmental quality, the slower the attenuation rate of the diffusion probability with distance, and the smaller the degree of diffusion probability attenuation.

4 Discussion

4.1 Mechanisms of diffusion characteristics

The results indicate that the diffusion of Yangling AS-

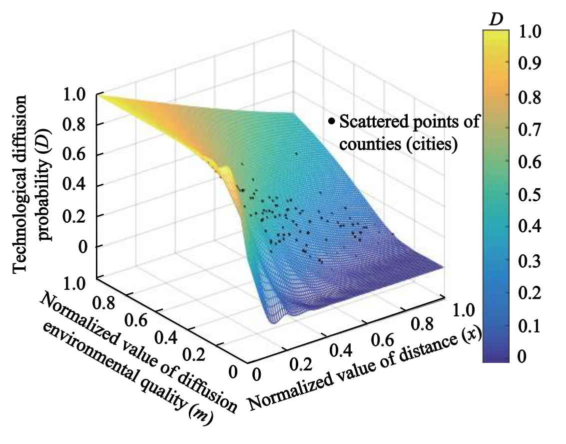

Fig. 6 The variation trend of technology adoption probability with distance and quality of technology diffusion environment

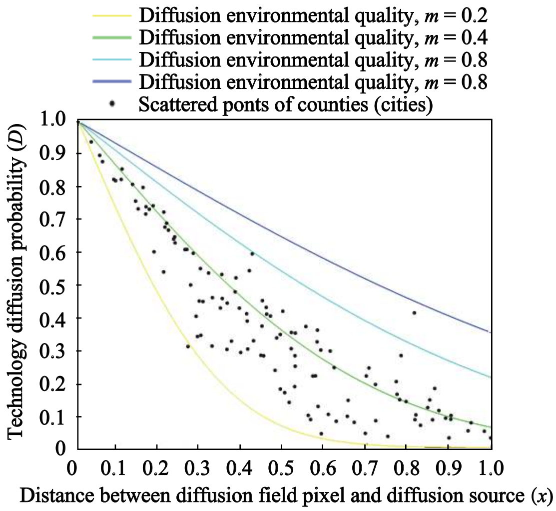

Fig. 7 The relevance between technology diffusion probability and the distance from ASTP under different diffusion environmental qualities

TP apple cultivation technology in the Loess Plateau apple advantageous production area is mainly characterized by the extended diffusion. The result is similar to the findings of Baptista (2000) and Bivand (2015), that a new technology will tend to spread in neighborhoods close to its point of adoption. Morrill (2005) explains this diffusion phenomenon by suggesting that repeated human interaction facilitates knowledge diffusion, but that human interaction decays with distance. Proximity can affect the frequency of communication, which enhances the exchange of information and ideas and promotes imitative behavior (Rogers, 1995). In addition, there are significant learning effects associated with the adoption of new technologies, and the geographic proximity and cultural similarities of neighboring regions can effectively facilitate the learning effect and thus the diffusion of new technologies (Kumar, 2014). Another possible explanation is that potential adopters in lagging regions can observe the introduction of new technologies in their neighboring leading regions. If the new technology is successful in the leading region, the risk of introducing the new technology in the lagging region is reduced, thus accelerating the diffusion of the new technology in the lagging region.

Hägerstrand (1967) suggested that in most cases, diffusion occurs through a combination of 'neighborhood contagion' and 'hierarchical transmission'. Walsh (1992) analyzed the spatial diffusion process of tractors in the Republic of Ireland and Northern Ireland and found the interaction of hierarchical and neighborhood effects produced a spatial pattern of tractor diffusion. Local attributes that were highly correlated with diffusion direction, speed, and path weakened the neighborhood effect and lead to the occurrence of the hierarchy effect. As shown in Fig. 5, a hierarchy effect occurs in counties (cities) with high diffusion environmental quality, such as Fuping County, which is a strong modern agricultural county in Shaanxi Province, with a high degree of large-scale agricultural operation and perfect agricultural infrastructure; Linyi County where rank effects occur, which is a provincial agricultural industry demonstration area with a high degree of agricultural industrialization. It is also the largest fruit-growing county in China and has developed a high-quality fruit industry.

We also found the spatial diffusion of ASTP apple planting technologies exhibits a banded diffusion characteristic along major transportation arteries. The possible explanation is that the enhanced road infrastructure encourages agricultural output (Tong et al., 2013). Differences in the diffusion environmental quality resulted in it being more effective areas with traffic arteries. We calculated the average agricultural development level of the five counties (Xiangfen, Yaodu, Hongtong, Huozhou, and Lingshi) through which the Beijing-Kunming Expressway passes (in Fig. 5 above) and the five counties around these counties (Guxian, Anze, Fushan, Daning, and Pu) that lack an expressway and found that the average agricultural development level of the first five counties was 1.383 times higher than the latter five. This result further validates the above explanation. Another possible explanation is that the development and improvement of transportation infrastructure facilitates the interregional exchange of people and goods and reduces the cost of interaction between technology extension workers and potential technology adopters, thus leading to the dissemination of knowledge and technology.

4.2 Suggestions for improving the technological diffusion efficiency of ASTP

We propose countermeasures to improve the technological diffusion efficiency of Yangling ASTP in terms of both technology diffusion path optimization and diffusion environmental quality improvement. The hierarchical diffusion indicates that counties (cities) with a high-quality diffusion environment can become nodes in the spatial diffusion network, and innovative technologies always start from these nodes and penetrate areas with a low socio-economic level. For example, in Changzhi County in in Fig. 5 above, Yangling ASTP diffusion jumps from Changzhi County to surrounding counties. Technology promoters can make full use of these nodes to strengthen the hierarchical diffusion effect, such as building experimental demonstration stations of the innovative technology at these nodes, promoting the balanced development of ASTP-driven agricultural areas. In addition, we found transportation infrastructure contributed to the heterogeneity of the technology diffusion environment in the study area. And the heterogeneity of the innovation absorptive capacity can widen the regional development gap and increase inequality (Zeng et al. 2019). Therefore, in the process of technology diffusion, technology promoters should pay attention to innovation absorptive capacity depressions that do not have major transportation arteries passing through them, such as Guxian and Anze counties. The technical linkage between the Yangling ASTP and these counties (cities) can be improved by organizing regular technical exchange training sessions in these counties (cities), such as focusing on training grassroots agricultural technicians and technology demonstrators and conducting large-scale farmer training in the field.

We concluded that ASTP technological diffusion has a strong distance attenuation effect. At the same time, we found that the attenuation rate of the diffusion probability decreases with distance, and the degree of attenuation of the diffusion probability decreases with an improvement in the diffusion environmental quality. This suggests that the frictional effect of distance can be decreased by improving the diffusion environmental quality. The Loess Plateau apple advantageous production area is located in the arid and semi-arid regions of China, where water scarcity is a major limiting factor for agricultural development (Chen et al., 2018). Farmland irrigation conditions can be improved through irrigation area expansion and renovation, as well as water source construction and efficient conservation. Also, it is necessary to pay more attention to farm irrigation infrastructure management, such as establishing a farmer-oriented farm irrigation input and management mechanism and clarifying the property rights of farm irrigation construction. Also, as a high-value agricultural product, apples have a high labor value condensation compared to grain and other bulk agricultural products, and technological progress in the apple industry is labor-intensive. However, under the combined push of productivity improvement within rural agriculture and the pull of industrialization and urbanization, a large number of rural laborers have moved to cities and engaged in non-agricultural industries (Zhang, 2018). Therefore, an effective way to enhance the technology diffusion environment in the study area is to improve workforce quality, change the traditional smallholder-based agricultural management system, such as quality training for farmers and the cultivation of new business entities. Supporting the complex new agricultural management system requires forming key enterprises as a leader, strong farmer family management, professional cooperation, and social services. Finally, information can shape problem awareness and attitudes, which are important factors in shaping farmers' outlooks and expectations on resource issues and technology choices (Lee, 2005). Therefore, improving the environment for farmers' information access would enhance the technology diffusion environment in the study area. Improving the information access environment can use diverse strategies like establishing experimental demonstration bases, farmer field schools, farmer associations or cooperatives, and strengthening the rural communication infrastructure.

4.3 Innovation in methodology

In terms of methodology, this study analyzed the technology diffusion law of ASTPs in a heterogeneous space by using the disaggregated spatial information. This method can be used to study the spatial expansion mode of technology not only under the combined effect of multiple types of spatial information, but also under the action of single spatial information because of regional characteristics such as information infrastructure, business innovation/entrepreneurship and consumer preferences, and regional policies that create different market-variously driving, facilitating, or inhibiting adoption. Quantitatively studying the impact of spatial information on the process of technology diffusion can help optimize the path of technology diffusion and improve the technological diffusion efficiency.

4.4 Limitations and future work

In synthesis, this paper contributes to the existing literature in three ways: Firstly, this study quantitatively identifies the key factors shaping the heterogeneity of the diffusion environment; Secondly, the study reveals the technology diffusion law of ASTPs in heterogeneous spaces; Lastly, our study provides an effective way to explain the spatial diffusion laws of technology using disaggregated spatial information. Nonetheless, the study also has some important limitations. First, because of limited data available for this study, county-level unit represent a single the diffusion field pixel. The administrative village is not only the basic management unit in the countryside, but also the basic economic and social unit formed by the rural population's life and production over a long period of time. Future research should try to collect social and economic data of village units to ensure the homogeneity of the diffusion environment within a single diffusion domain. Second, technology diffusion is affected by both temporal and spatial heterogeneity. This study solely addresses the impact of heterogeneous space on technology diffusion. The effect of temporal heterogeneity on technology diffusion can be further studied to determine the law of technology diffusion in ASTPs under the heterogeneity of time and space.

5 Conclusions

Although existing research has also focused on the effects of environmental heterogeneity on agricultural technology diffusion, there is a lack of a systematic approach to uncover the patterns of agricultural technology diffusion in heterogeneous environments. In this study, presented a framework for analyzing the law of ASTP technology diffusion in heterogeneous space. This is an integrating framework between geographic space, the process, and entities which are affected by the process. Within this framework, we first constructed a comprehensive index system to evaluate the diffusion environmental quality, and then introduce HSDM into the calculation of the technology diffusion probability of ASTP, and provide a detailed description of the principles and parameter estimation process of HSDM applied to the technology diffusion of ASTP.

The results suggested that the technological diffusion environment of the main apple-producing areas in the Loess Plateau showed strong spatial heterogeneity caused by structural factors such as climate, topography, and the strength of external transportation links. This showed that differences in the diffusion environment in the case area were mainly caused by the natural environment. Except for external transportation factors, the social and economic conditions that affect agricultural technology diffusion in the case area were not significantly different. We also found that the Yangling ASTP apple cultivation technology showed a spatial diffusion pattern based on expansion diffusion, supplemented by banded diffusion and hierarchical diffusion. Based on the relationship between the diffusion environmental quality, the standard distance, diffusion probability, and the technical diffusion of ASTPs had a strong distance attenuation effect and the improved diffusion environment quality can attenuate the frictional effect of distance. The heterogeneity of the diffusion environment increases the difficulty of agricultural technology diffusion. Therefore, the revelation of agricultural technology diffusion laws in heterogeneous environments can provide information for decision makers to propose targeted technology diffusion strategies.

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