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Research article

Spatial effects of the agricultural ecosystem services based on environmental kuznets curve in Mengyin county, China

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ABSTRACT

Worldwide most agroecosystems effort to increase production and yields and leads to damages of a series of non-provisioning ecosystem services (ESs). To fill in the knowledge gaps pertaining to the understanding of complex relationship between agricultural harvests and other ESs, therefore this study aims to estimate the existence of Environmental Kuznets Curve (EKC) for agricultural ESs by incorporating the spatial factors. Based on the test of the spatial autocorrelation of agricultural ESs, the estimation results of spatial model are compared with general regression to explain the spatial effect of agricultural ESs. The results show that (1) contrary to expectation, the curve of the nonlinear relationship between agricultural ESs and annual household income is an inverted U-shape, and not an upright U-shape; (2) compared to non-spatial model, the turning point of the inverted U-shaped curve for agricultural ESs under the direct effect would happen earlier and happen later under the indirect effect; (3) years of formal education, vegetation coverage of field margin and cultivated land area have significantly impact on local agricultural ESs, and local perennial crops has significantly impact on agricultural ESs of neighboring villages. Results of this study have a promising application prospect to promote sustainable development of agriculture.

1. Introduction

Global social and economic development and climate change are affecting the ecological environment of China, such as resulting in biodiversity loss, ecosystems destruction and land resources degradation, especially the agroecosystems that comprise roughly half of the global land surface [1,2]. To cope with anthropogenic pressures, most agroecosystems effort to increase production and yields typically through intensification and expansion areas, that leads to damages for a series of ecosystem services (ESs), such as the

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biogeochemical nutrient cycles, regulation of soil and water quality, pollination and cultural services [3–5]. Yet, sustainable and resilient agroecosystems should have ability to deliver an entire package of ESs, rather than provisioning services alone [2,6]. Therefore, the information that how to coordinate the tradeoff relationships of agricultural harvest and other ESs can be used by researchers and policy makers to increase both economic and environmental wealth in a sustainable way [7,8]. Recently, increasing efforts that explore the relationship between economy and environment to implement sustainable development are being attached much importance gradually by public and academic concern [9,10]. Among many researches on this topic, the most widely supported is the Environmental Kuznets Curve (EKC) hypothesis [11,12].

Originated from simulation of Kuznets curve about the relationship income inequality and economic growth [13], the EKC hypothesis was proposed to examinate the impact of economic development on the degree of environmental pollution [11]. In the general sense, the EKC hypothesis reflects the idea that, economic growth brings the natural environment deterioration to some extent and improvement after a certain turning point, postulating that the relationship between environmental degradation and economic growth is an inverted U-shaped curve [14]. Numerous empirical studies share a common situation based on the EKC hypothesis, which suggests that the impacts of economic development on indicators of environmental degradation differ significantly depending on the stages of economic development and follow an inverted U-shaped curve over two stages: the initial stage of economic development characterized by a structural change from an agricultural-based economy to an industrial-based economy and the next phase of economic development characterized by a structural change from a resource intensive economy to a service-based technology-intensive economy [14–16]. In the most existing researches, single-variable environmental indicators were employed as proxies of environmental degradation, which takes into account three main categories: air quality indicators such as sulfur dioxide [17], carbon dioxide [18], fine particulate matter of 2.5 mm or smaller [12] and other air pollutants; water quality indicators such as total phosphorus [19], waste water [20], water pollution discharge-chemical oxygen demand [21] and other water pollutants; other quality indicators such as biodiversity risk [22], land consumption [23], chemical fertilizer or pesticide [24]. Actually, these single-variable indicators of environment degradation are a multifaceted problem and have some definite relations with different stages of economic development, which can be explained in one such EKC relation [14,25]. From the circumstance about agrarian economies exploiting more natural resources and ESs, the analysis of environment-economy about agroecosystem should be valuable to further consider the problem of under-provision of a positive externality (ecosystem services), rather than the problem of the over-supply of a negative externality (pollution) [26–28]. In addition, the integrative environmental index based on the ESs can be used within research on sustainable development to detect the problem of under-provision of a positive externality in agroecological environment [29,30].

Another important problem is how to quantitatively link the ESs to the maintenance of sustainable agroecosystems based on EKC hypothesis. On the one hand, a variety of complex ESs are connected and impacted by materials, energies and information flows, making the supply of ESs move across agroecosystems or even among regional boundaries [2,31,32]. On the other hand, local agricultural production process also exists spatial autocorrections, meaning that local ESs are likely to be affected by neighboring agricultural production [33,34]. In other words, the multiple ESs in neighboring agroecosystems are more likely to be closely connected to each other [35,36], which is in line with First Law of Geography (everything is related to everything else, but near things are more related to each other) [37]. Specifically, the spatial effect brought by the inter-relationship among regions would be fell into two types: spatial dependence (agroecosystems of delivering multiple ESs are regionally agglomerated to a certain degree) and spatial heterogeneity (there is a significant influence of location factors on the spatial distribution of delivery of multiple ESs from agroecosystems) [38–41]. Furthermore, both spatial effects may accurately represent the complex forms of spatial structure [42]. However, spatial dependence and spatial heterogeneity are closely related and difficult to distinguish [12]. Thus, ignoring spatial correlation would lead to the biased shape of EKC, which will, to a certain extent, constrain the collaborative governance of cross-regional agricultural

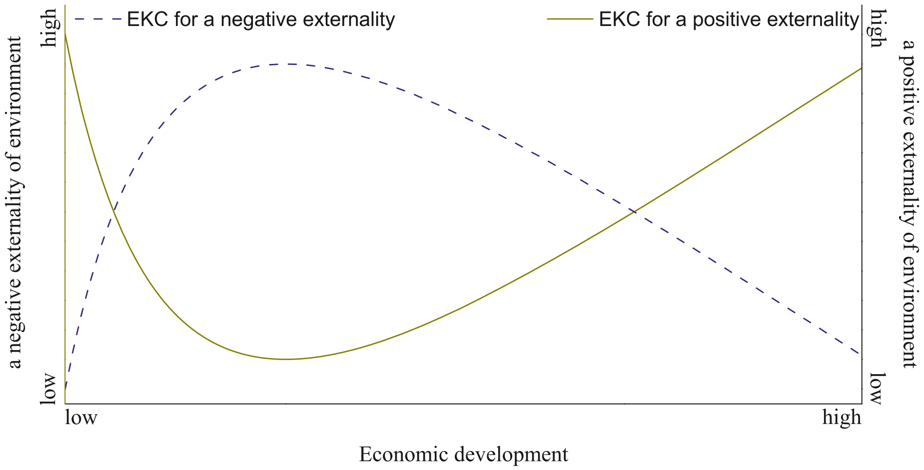

Fig. 1. Schematic of an inversed U-shaped EKC hypothesis (the dash line) for negative externality and an upright U-shaped EKC hypothesis (the solid line) for positive externality (adapted from Ref. [48]).

practices and agri-environmental protection [36,43]. Compared to conventional statistical methods (such as gray correlation degree analysis, multiple regression models et al.), spatial econometrics can eliminate spatial errors in the measurement results to the greatest extent by taking spatial correlation among the locations of individual observations [24]. To date, only a few studies have applied spatial econometrics methods to measure the EKC by linking with spatial correlation. For instance, the spatial econometric model is chosen in examination of the existence of EKC of $PM_{2.5}$ pollution in the Beijing-Tianjin-Hebei region of China [12]; considering spatial interdependences across countries within the European Union, the EKC relationship between water quality and income is investigated with an inverted *N*-shaped relationship [44]; empirical results, based on the spatial autocorrelation analysis, verify a U-shaped EKC relationship of urbanization level on ESs [45]. However, the predictions of spatial effects of the agricultural ESs based on EKC hypothesis are extremely rare. Therefore, agroecosystems management should consider the impact of spatial correlation of ESs to optimize their integrated effects.

In essence, agroecosystems as complex adaptive systems address multiple ESs. Finding ways to support provisioning services which synergize other ESs requires transformations involving technological, socio-economic and political changes [46,47]. To fill in the knowledge gaps pertaining to the understanding of complex relationship between agricultural harvest and other ESs, therefore this study aims to estimate the EKC of the agricultural ESs by incorporating the spatial factors. This study differs from standard EKC models which talk about an inverted U-shaped curve, however, by considering agricultural ESs, it focuses on the problem of under-provision of a positive externality, which varies along a U-shaped curve (Fig. 1). In the context of intensified agricultural systems, the EKC assumption here is that a fast decrease and subsequently a slow increase of a positive externality of agroecosystems are accompanied by an increase of agricultural economy (for example, the solid line in Fig. 1). Consequently, this study aims to answer the following research questions: (1) Is there spatial effect of agricultural ESs in Mengyin County, Shandong Province? (2) Does the agricultural ESs and economic development conform to an upright U-shaped EKC hypothesis? If a statistically significant curve exists, does its inflection point occur? Where is the inflection point? (3) What's the impact of spatial effect on the relationship between the agricultural ESs and economic development, how agricultural characteristics affect the ESs, and what are the underlying meanings?

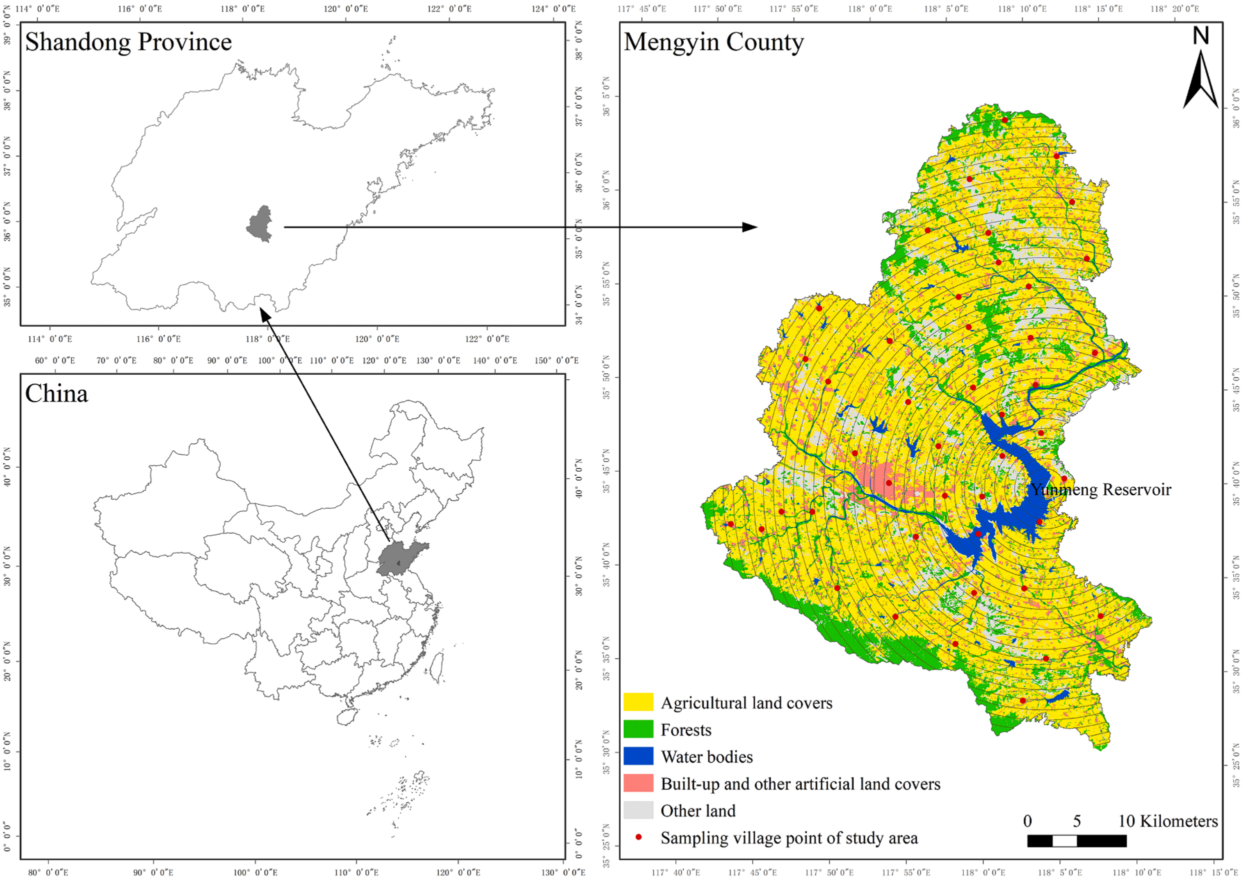

Fig. 2. The location of the study area and sampling villages (adapted from Ref. [49]).

2. Materials and methods

2.1. Study area and data

The study was carried out in Mengyin County, Shandong Province, China (Fig. 2). It belongs to Linyi City of Shandong Province, which is located in the central and southern part of Shandong Province, the hinterland of the Taiyi mountains and the nightside of Mengshan mountain. It spans 117° 45′ - 118° 15′ E and 35° 27′ - 36° 02′ N. The maximum distance between North and South is 65.4 km, and the maximum distance between East and West is 45.8 km. The total area is about 1601.6 km^2, accounting for 9.3% of the total area of Linyi city. Mengyin County's agriculture is particularly developed, and new orchards are rapidly expanding. More than half of the county's land is used for agricultural production. The resident population is 485,300, most of which are agricultural population. Thus, attaching importance to the spatial effect of agricultural ESs in study area offers an interesting approach to promote the coordinated agriculture development.

The research data involves 13 ESs, which are pollination, biological pest control, water purification, water regulation, maintaining healthy waterways and reservoirs, waste assimilation, natural hazard regulation, recreation and aesthetic values, cultural heritage values, discriminating features and sense of place, maintenance of soil fertility and health, maintenance of natural genetic diversity, and maintenance of semi-natural habitat respectively. The data of ESs are scored for each service in the form of a questionnaire, and the score range is 1–10. In addition, the study also investigates the general personal characteristics and farming characteristics of farmers. The research method adopts stratified sampling and randomly selects the surveyed farmers. The specific methods are as follows: (1) 1 km buffer zone has been established around Yunmeng reservoir, and a total of 40 buffer zones have been established. (2) one or two villages are randomly selected for each buffer zone, and a total of 44 villages are selected. (3) 3–5 households are randomly selected from each village and a total of 174 households were surveyed. Pre-investigation (2014) was conducted before formal investigation (2015) in Mengyin County. Moreover, the data of annual household income (AHI) were collected from the Mengyin Statistical Yearbooks and farm households survey (2015).

Each service is normalized using a logarithm based on 10 and calculated using the following formula (1) [50]:

$$I_s = \log_{10} I \tag{1}$$

where I_s the normalized value of each service, and the range is 0–1; I is the value of each service, and the range is 1–10.

The index of integrative ecosystem services (*IES*) [21] can well reflect the overall level of these 13 ESs, and is obtained by summing up the 13 normalized services (each service is normalized to lie between 0 and 1 by Eq. (1)) as formula (2):

$$IES = \sum\nolimits_1^n I_s \tag{2}$$

where n is the number of ESs, which is 13 in this study. *IES* represents an overall level of the obtainment of the 13 services. High values thus indicate the relatively high obtainment of multiple services, while low values indicate the opposite [30,51].

2.2. Spatial analysis

When doing spatial analysis, it is necessary to check whether the research variables have spatial correlation. Moran's *I* index is considered to be one of the best choices to test spatial autocorrelation. Its value is the slope of the linear regression line of Moran scatter plot [24,52,53]. Formula for calculating Moran's *I* index is expressed as formula (3) [24]:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \overline{y})\left(y_j - \overline{y}\right)}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum\nolimits_{i=1}^{n} (y_i - \overline{y})^2} \tag{3}$$

where n is the number of villages, which is 44 selected with a stratified sampling method in this study (Fig. 2). Y_i and y_j are the regional *IES* of region i and j, respectively. ^{-}y is the average *IES* of Mengyin county. W_{ij} is the element at row i and column j of the spatial weight matrix W. Eq. (3) shows that Moran's I index ranges from −1 to 1. In addition, it indicates a positive spatial autocorrelation with the values of Mora's I between 0 and 1, and a negative spatial autocorrelation between −1 and 0 and no spatial correlation at 0.

The spatial weight matrix W can be defined in many different forms according to distance and proximity [38,54]. Furthermore, some researches compare different spatial weight matrices to identify the spatial weight matrix that best fits the data [55,56]. This research, based on characteristics of data, adopts k-Nearest Neighbors spatial weight, for which the setting principle is as formula (4):

$$w_{ij} = \begin{cases} 1, \mathit{if\ canton} \text{ to the set of the nearest neighbours;} \\ \qquad 0, \mathit{otherwise}. \end{cases} \tag{4}$$

Here, the spatial weights matrix W is an n × n positive matrix, where n is the number of villages, and W is row-normalized to sum its rows to unity [12,38].

2.3. EKC model

From the literature reviewed, the majority of studies demonstrate that farmer household characteristics, such as years of formal education (EDU) [57,58] and farmland characteristics, such as cultivated land area (CLA) [59,60], crop type [61,62] and field margin [63,64] have a significant effect upon agricultural ESs. The crop types of study area can be categorized into two types: annual crops (AC) and perennial crops (PC), thus the dummy variable *PC* is included into the model for analyzing to capture crop types effects. As vegetation coverage of field margin (VCFM) is a representative indicator for field margin, the EKC model is set as formula (5):

$$IES_i = \beta_0 + \beta_1 LNAHI_i + \beta_2 (LNAHI_i)^2 + \beta_3 EDU_i + \beta_4 CLA_i + \beta_5 PC_i + \beta_6 VCFM_i + \varepsilon_i \tag{5}$$

where IESi donates index of integrative ecosystem services; LNAHIi is the natural log of annual household income; EDUi stands for years of formal education; CLAi refers to cultivated land area; PCi represents perennial crops, which equals one if crop types be categorized perennial crops, otherwise zero; $VCFM_i$ is the vegetation coverage of field margin; β_0 is the constant term; β_1, β_2, β_3, β_4, β_5 and β_6 are the estimated coefficients of explanatory variables; $i = 1, 2, \ldots, 44$, representing villages; ε_i is random error terms. In the model, *LNAHI* and its squared term are subsumed into the equation to identify the turning point of possible existence for EKC. This model is evaluated with ordinary least squares (OLS) method by using R software. The descriptive statistics results of variables are summarized in Table 1.

To investigate the spatial spillover of *IES*, with R software, the spatial models are developed based on OLS method by introducing the spatial weight matrix into the regression. The relationship of spatial models can be presented by Fig. 3. Specifically, a spatial error model (SEM) accounts for spatial error dependency, a spatial lag model (SLM) depicts spatial dependency in dependent variable, a spatial lag of X model (SLX) introduces the spatial lag into each independent variable, and a spatial Durbin model (SDM) incorporates in both spatial lagged dependent variable and independent variables [38,56,65]. Therefore, the spatial models in this study can be expanded based on the non-spatial regression model of Eq. (5) as formula (6-9) [38,65]:

Spatial Error Model (SEM):

$$IES = \beta X + \mu \text{ with } \mu = \lambda W\mu + \varepsilon \tag{6}$$

Spatial Lag Model (SLM):

$$IES = \rho WIES + \beta X + \varepsilon \tag{7}$$

Spatial Lag of X Model (SLX):

$$IES = \beta X + \theta WX + \varepsilon \tag{8}$$

Spatial Durbin Model (SDM):

$$IES = \rho WIES + \beta X + \theta WX + \varepsilon \tag{9}$$

where *IES* is the *N*-by-1 vector of dependent variable (*IES* values obtained by Eq. (2)) in villages of the study area. *X* is the *N*-by-M matrix of independent variables (i.e., *LNAHI, LNAHI*^{2}*, EDU, CLA, PC, LNVCFM* values and constants) and β is the corresponding regression coefficient matrix. μ and ε are spatially autoregressive error terms and random error terms, respectively. λ, ρ and θ reflect the scalar parameter reflecting the strength of spatial dependence in the error term, dependent variable and independent variables, respectively. W represents a spatial weight matrix and the elements of the matrix W is computed by Eq. (4). Eqs. (5)–(9), the comparison of model performance among OLS, SEM, SLM, SLX and SDM is based on three statistical parameters: R^2, Log likelihood (LogL) and Akaike information criterion (AIC). When the model better explains variance of the dependent variable, R^2 and LogL tend to be higher, while AIC tend to be lower. In other words, a better optimizing model is indicated by higher statistical parameter of R^2 and LogL, as well as lower AIC.

2.4. Redundancy analysis based on spatial model

The IES data can be modeled as a multivariate object, which has the advantage for directly taking into account of multiple ESs. To investigate the relationship between multiple ESs and household and farmland characteristics (represented by the four characteristic

Table 1
Descriptive statistics results for variables.

Variables	Abbreviation	Mean	Min.	Max.	Std.
Index of integrative ecosystem services	*IES*	7.64	4.16	9.45	0.97
The natural log of annual household income	*LNAHI*	10.27	8.37	11.51	0.83
Years of formal education	*EDU*	7.14	3.00	12.50	1.91
Cultivated land area (ha)	*CLA*	0.33	0.07	1.98	0.29
Annual crops, which equals one if crop types be categorized annual crops, otherwise zero	*AC*	0.18	0.00	1.00	0.39
Perennial crops, which equals one if crop types be categorized perennial crops, otherwise zero	*PC*	0.82	0.00	1.00	0.39
the vegetation coverage of field margin (%)	*VCFM*	29.13	13.75	59.50	8.39

Note: annual household income in this study refers to annual household' farming income from farmlands.

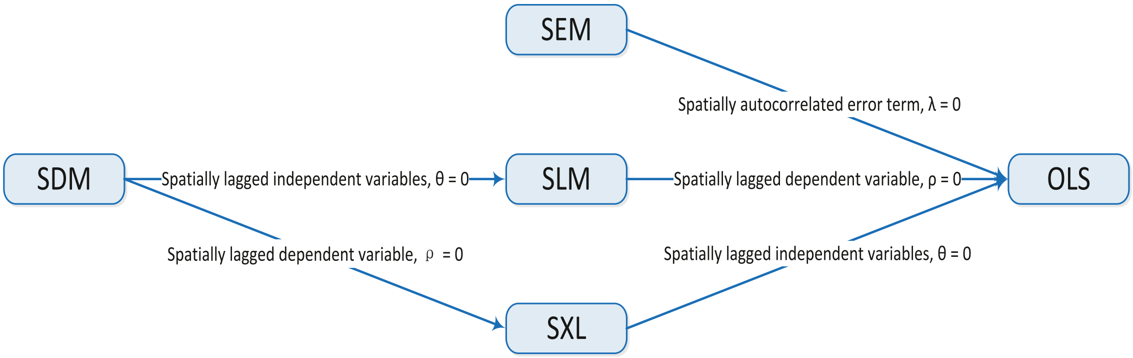

Fig. 3. Relationship of the models.

variables), this study performs a redundancy analysis (RDA) with R software. RDA has been suggested as an appropriate quantitative method to verify whether ESs can be explained by a set of driver factors [66,67]. Specifically, the correlations are represented with RDA biplot, in which the relationships (between ESs and characteristic metrics, between ESs and villages, among multiple ESs themselves, among characteristic metrics themselves) are reflected.

As above, a four-step approach of analysis is conducted to investigate the spatial effect of agricultural ESs: (1) calculate an integrative index of ES based on deriving 13 individual ecosystem service (see more details in Section 2.1); (2) the Moran's I statistic (-) is employed to test and visualize the spatial autocorrelation of IES (see more details in Section 2.2); (3) after confirming the existence of spatial dependence, the spatial regression models are used to evaluate the driving factors of IES (see more details in Section 2.3); (4) for 13 ESs, RDA is used to multivariate response characteristic variables and their interactions help to produce new insights into the agricultural policies and their impacts. The analysis process of this study is shown as Fig. 4.

3. Results

3.1. Spatial autocorrelation test of IES

Moran's I index is represented by Moran scatter plot to test the autocorrelation of IES in the study area. In following Fig. 5, the horizontal axis represents the deviations of IES observation of the respective districts, while the vertical axis represents the average deviations of their neighbors. The scatter diagram is divided by the horizontal and vertical axes into four quadrants: quadrant I (the high-high situation in upper right of Fig. 5 means that districts with high IES are bordered by districts with high IES) and quadrant II (the low-low situation in lower left) indicate positive spatial dependence, while quadrant III (the low-high situation in upper left) and quadrant IV (the high-low situation in lower right) exhibit negative spatial dependence. The slope of the regression line is the value of Moran's I.

As shown in Fig. 5, the values of Moran's I, Z-score and p-value are 0.3148, 3.5614 and 0.0002, respectively. More than two-thirds of the 44 villages appear in the quadrant I and III, and the Moran's I index is significantly positive. These results suggest that there is positive spatial dependence of the IES across the villages in study area and higher value of Moran's I indicates stronger impact of IES from neighboring villages on local villages.

3.2. Results of regression analysis of EKC

In this study, first of all, the influence of *LNAHI* on *IES* is analyzed by OLS without considering the spatial effect. Based on the results (the second column of Table 2), the coefficients of *LNAHI* and $(LNAHI)^2$ are positive and negative, both which pass the significance level of 5%, indicating an inverted U-shaped curve with turning point of 21,327 yuan. Among the characteristic variables, *EDU* and *VCFM* have significant positive impacts at 5% and 10% level, respectively, while *CLA* has significant negative at 1% level. Further, the results in the second column of Table 2 indicate that if the years of formal education increase 1 year, the *IES* will rise 0.135; if the cultivated land area rises 1 hm^2, the *IES* will decline 1.554; if the vegetation coverage of field margin go up 1%, the *IES* will increase 0.025.

Different from the OLS estimation, the spatially autocorrelated error term, the spatially lagged dependent variable, spatially lagged independent variables and both the spatially lagged dependent and independent variables are introduced in the SEM, SLM, SLX and SDM to explore the spatial effects of IES, respectively. The results show that SEM, SLM, SLX and SDM perform better than OLS for *IES* regressions and the SDM is chosen as the most preferable model specification, as R^2 and LogL values increase, and AIC values decrease (the 16–18 row of Table 2). Thus, regression coefficient estimates of the SDM should be focused to interpret.

The results in the six column of Table 2 show that the coefficients of *LNAHI* and the quadratic of *LNAHI* are positive and negative, both which pass the significance level of 1%, indicating an inverted U-shaped curve of *IES*. The results also show that the estimated coefficient of *EDU* is 0.093 with 10% level significance indicating that an increase of 1 year of formal education would bring *IES* to increase 0.093; the estimated coefficient of *CLA* is −1.343 with 0.1% level significance indicating that a rise of 1 ha cultivated land area

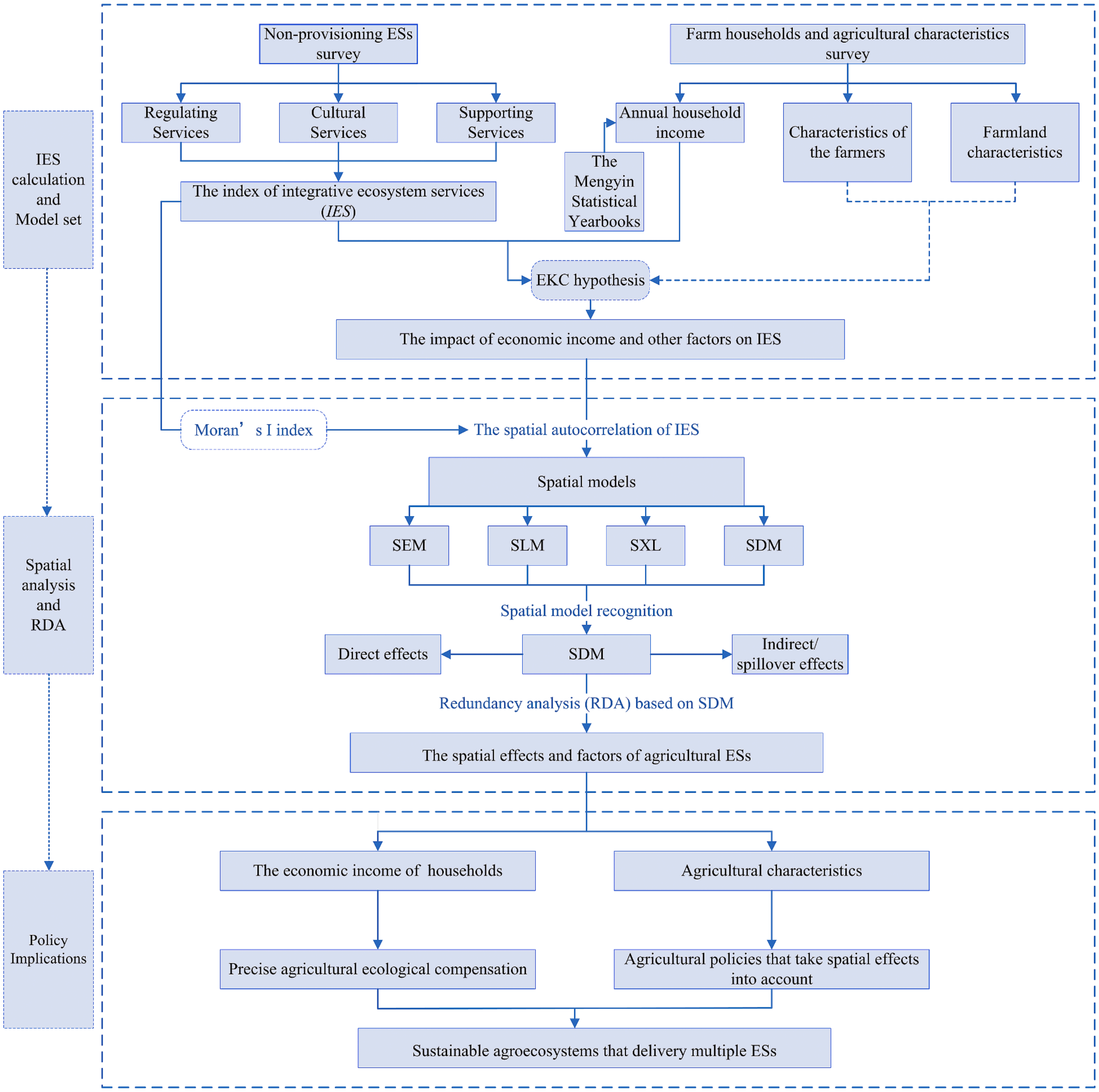

Fig. 4. Flow chart of research.

would bring *IES* to decline 1.343; the estimated coefficient of *VCFM* is 0.017 with 10% level significance indicating that an ascent of 1% the vegetation coverage of field margin would bring *IES* to rise 0.017.

As shown in the six column of Table 2, the estimated coefficients of spatially lagged independent variables (W*X) reflect how these independent variables in neighbors affect the local IES. Both the estimated coefficients of *LNAHI* and $(LNAHI)^2$ pass the significance level of 5%, implying that the spillover effect of farmers' annual household income in the neighboring regions will significantly affect the agricultural ESs of local region. In addition, only the coefficient of W*PC is positive and passes the significance level of 5%, which reveals that perennial crops of the neighboring regions by contrasting annual crops will positively affect the agricultural ESs of local region. As the 15 row of Table 2, the Rho (ρ) of lagged dependent variable is positive at 5% significant level, revealing that *IES* of a certain region would be influenced by neighboring regions. In other words, a higher supply of agricultural ESs in the neighboring regions will stimulate the agricultural ESs in a place, forming an accumulation situation of "high-high" or "low-low".

The regression coefficients of the SDM not only capture the direct effects of the independent variables on the dependent variable, but also subsume the feedback effects. Therefore, it is necessary to calculate the turning points of EKC for *IES* from the SDM by identifying the direct effect (the effect of regional explanatory variable on the dependent variable in the same region), the indirect

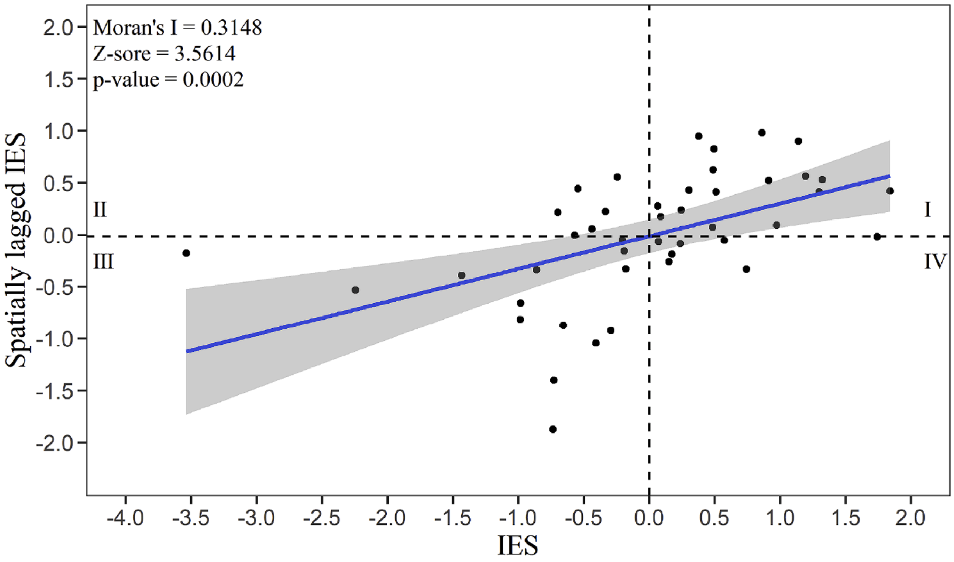

Fig. 5. Moran's I scatterplot of IES (the index of integrative ecosystem services).

Table 2
The estimation results of EKC models of agricultural ecosystem services.

Determinants	OLS	SEM	SLM	SLX	SDM
Constant	−35.032 * (−2.158)				
LNAHI	8.429 * (2.566)	6.712 * (2.317)	6.632 * (2.431)	7.011 * (2.331)	6.980 ** (2.778)
(LNAHI)2	−0.422 * (−2.557)	−0.336 * (−2.312)	−0.330 * (−2.400)	−0.357 * (−2.367)	−0.355 ** (−2.819)
EDU	0.135 * (2.189)	0.081 (1.552)	0.064 (1.218)	0.102 · (1.768)	0.093·(1.885)
CLA	−1.554 ** (−3.347)	−1.410 *** (−3.751)	−1.601 *** (−4.237)	−1.334 ** (−3.032)	−1.343 *** (−3.647)
_PC_	−0.294 (−0.894)	−0.538 · (−1.875)	−0.497 · (−1.842)	−0.101 (−0.309)	−0.142 (−0.515)
VCFM	0.025 · (1.832)	0.015 (1.291)	0.017 (1.520)	0.019 (1.577)	0.017 · (1.709)
W* LNAHI				15.569 · (2.034)	14.072 * (2.085)
W* (LNAHI)2				−0.736 · (−1.964)	−0.663 * (−2.004)
W*EDU				0.028 (0.210)	0.010 (0.088)
W* CLA				−1.459 (−1.400)	−1.249 (−1.348)
_W*PC_				1.039 · (1.708)	1.045 * (2.053)
W* VCFM				0.024 (0.792)	0.019 (0.700)
Spatial lag (λ)		0.531 *** (3.451)			
Spatial lag (ρ)			0.466 *** (3.848)		0.127 * (2.244)
R^2	0.581	0.612	0.653	0.747	0.749
LogL	−42.137	−40.437	−37.970	−30.989	−30.851
AIC	100.274	98.873	93.940	91.978	91.702
Inflection point	21,741				

Notes: · $p \leq 0.1$; *$p \leq 0.05$; **$p \leq 0.01$; ***$p \leq 0.001$. Numbers in parenthesis are the corresponding z-statistics for the SEM, SLM and SDM, and the t-statistic for the OLS model and SLX.

Table 3
The direct, indirect and total effects estimates based on SDM.

	Direct effects	Indirect/spillover effects	Total effects
LNAHI	7.372 ** (2.864)	16.749 * (2.021)	24.121 ** (2.629)
(LNAHI)2	−0.373 ** (−2.902)	−0.793 · (−1.957)	−1.166 ** (−2.586)
EDU	0.093 · (1.834)	0.025 (0.124)	0.118 (0.671)
CLA	−1.380 *** (−3.515)	−1.589 (−1.405)	−2.969 * (−2.201)
_PC_	−0.115 (−0.358)	1.149 · (1.689)	1.034 (1.387)
VCFM	0.018 · (1.686)	0.023 (0.707)	0.041 (1.119)
Turning point (yuan)	19,575	38,581	31,053

Note: · $p \leq 0.1$; *$p \leq 0.05$; **$p \leq 0.01$; ***$p \leq 0.001$. Numbers in parenthesis are the corresponding z-statistics for the direct, indirect and total effects. Estimates are based on SDM in Table 2.

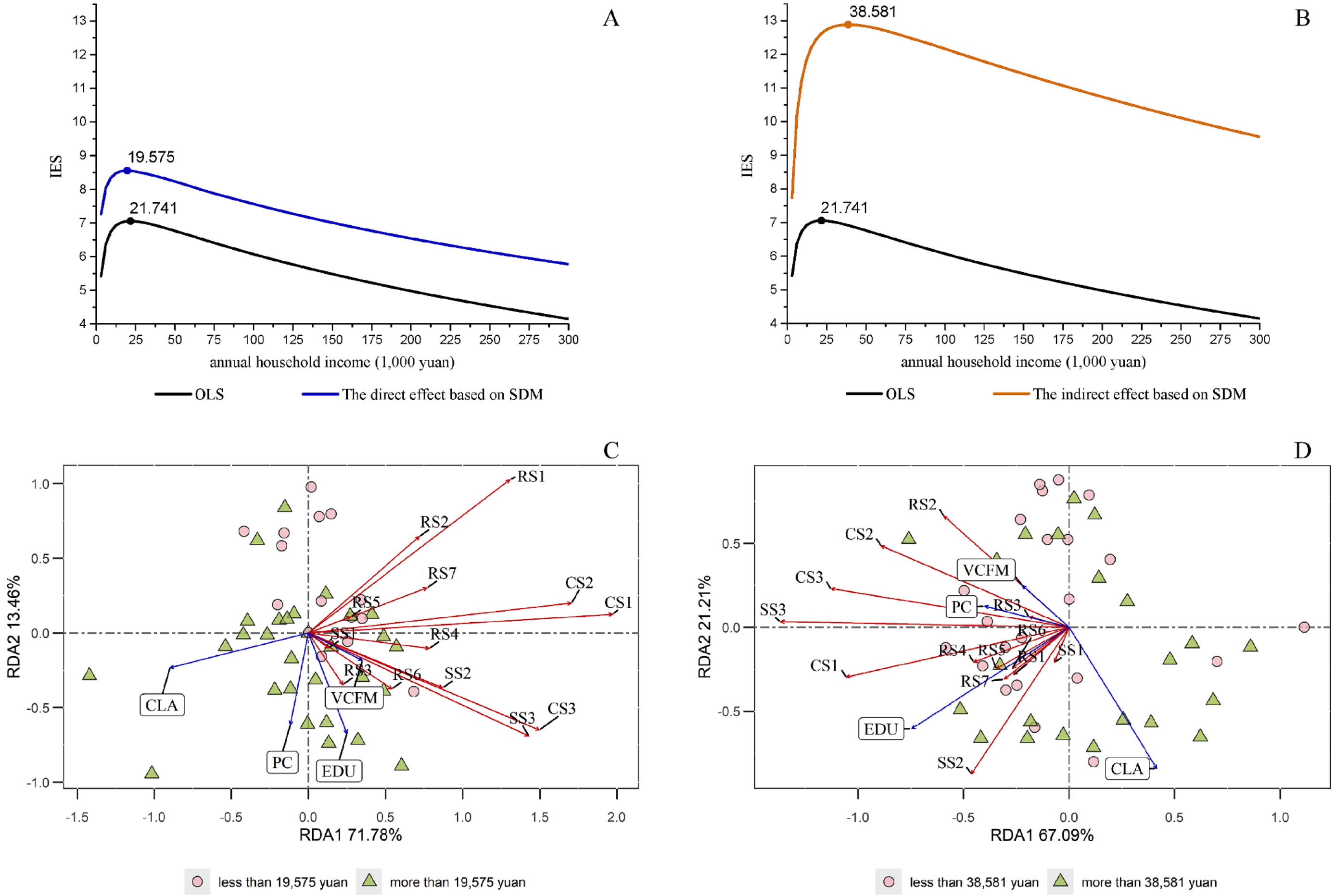

Fig. 6. Relationships among the multiple ESs and characteristic variables based on the direct and indirect effects in SDM. The inverted U-shaped curve of IES based on the direct effect (A) and indirect effect (B). The turning point calculated under the OLS model is 21,327 yuan, and the turning points calculated under the direct and indirect effects are 19,575 and 38,581 yuan. Redundancy analysis (RDA) biplots illustrate the relationship between the regional multi-ESs and characteristic variables in the same region (C) and explain the relationship between the multi-ESs in neighboring region and regional characteristic variables (D). The ESs are abbreviated as follows: regulating services (RS1 = pollination, RS2 = biological pest control, RS3 = water purification, RS4 = water regulation, RS5 = maintaining healthy waterways and reservoirs, RS6 = waste assimilation and RS7 = natural hazard regulation); cultural services (CS1 = recreation and aesthetic values, CS2 = cultural heritage values and CS3 = discriminating features and sense of place); supporting services (SS1 = maintenance of soil fertility and health, SS2 = maintenance of natural genetic diversity and SS3 = maintenance of semi-natural habitat).

effect (the effect of local explanatory variable on the dependent variable in neighboring region) and the total effect (the sum of direct and indirect effect). The coefficients of spillover effect (indirect effect) differ from W*X in that, the coefficients of spillover effect reflect how regional explanatory variable affect the dependent variable in neighboring regions, while the coefficients of W*X reflect how explanatory variables of neighboring regions affect the regional dependent variable.

As reported in Table 3, the coefficients of LNAHI and $(LNAHI)^2$ in the direct, indirect and total effects are significantly positive and negative, respectively, which is similar to the results estimated by the OLS (the second column of Table 2) and indicates an inverted U-shaped curve. Under the SDM with spatial effects, the inflection point calculated under the direct effect is 19,575 yuan, the indirect effect is 38,581 yuan and the total effect is 31,053 yuan (Table 3). Compared to the turning point of 21,327 of OLS estimation in Table 2, the value of inflection point in direct effect is very close to OLS estimation, while the value of inflection point in the total effect would be higher because it accounts also for the indirect effect. Among the characteristic variables, it is noteworthy that the coefficients of *EDU*, *CLA* and *VCFM* in direct effect pass the significance test, while only the coefficient of *PC* in indirect effect is significant.

3.3. Results of redundancy analysis with spatial effects considered

To illustrate the results more intuitively, inverted U-shaped curves of direct and indirect effect estimations of SDM are fitted and compared with OLS estimation, as well as four regional characteristic variables affecting the spatial distribution of 13 ESs in the same and neighboring region are identified by RDA. The permutation tests indicate statistically significant association between regional characteristic variables and ESs in the same and neighboring region (p-values = 0.001 and 0.012 from 999 permutations, respectively). The explanatory variables of RDA account for 25.63% and 18.84% of the variation in regional and neighbor ESs, while the first two axes explained 85.24% and 88.30% of the explanatory variables of RDA. The biplots of the RDA represent the first two axes and suggest that regional and neighbor ESs exhibit contrasting relationships with regional characteristic variables (Fig. 6 C and D).

As shown in Fig. 6C, the first axis of the RDA (25.63% * 71.78% = 18.40% of the variance) reveals, based on the positive scores, an association of 13 ESs highly related with characteristic variables such as the *EDU* and *VCFM*. While the negative scores of the first axis are associated with the CLA. These results are consistent with the analysis of SDM in direct effects (Table 3). As shown in Fig. 6 A and C, sampling villages could be grouped into two categories by the turning point of 19,575 yuan. The second axis of the RDA (25.63% * 13.46% = 3.45% of the variance) reveals a gradient across the two categories of villages (Fig. 6C). The most negative scores are closely associated with the villages (more than 19,757 yuan) relative to supporting services and the four characteristic variables.

The biplot of the RDA present that regional characteristic variables exhibit contrasting relationships with ESs in the neighboring regions (Fig. 6 D). The first axis of the RDA (18.84% * 67.09% = 12.64% of the variance) reveals an association 13 ESs with the *EDU*, *PC* and *VCFM* on the negative loads. Especially the *PC* mostly responds a positive influence to neighbor regulating services. As shown in Fig. 6 B and D, sampling villages could also be grouped into two categories by the turning point of 38,581 yuan. The two categories of the villages site position along the first axis of RDA compared with the second axis (18.84% * 21.21% = 4.00% of the variance) reveal a more noticeable gradient (Fig. 6 D).

4. Discussion

4.1. EKC analysis of agricultural ESs

This study analyses the nonlinear relationship between agricultural ESs and annual household income. The EKC hypothesis of agricultural ESs assumes that it talks about a U-shaped curve to focus on the problem of under-provision of a positive externality [28,48]. The results do not support a U-shaped hypothesis of EKC for agricultural ESs (Table 2). Contrary to expectation, the curve is an inverted U-shape, and not a U-shape, which implies that before the inflection point, an increase in annual household income corresponds to an increased delivery of agricultural ESs, while after the inflection point, a growth in annual household income will be associated with a higher impairment rate of the delivery of agricultural ESs. This show that farmers do benefit from a variety of ESs, while their activities may strongly influence the delivery of agricultural ESs, ultimately resulting in a loss of resilience and lack of sustainability in agroecosystems [2,68].

In contrast to natural habitats and social systems, these results are consistent with the idea that agroecosystems could be described as semi-natural habitats and socio-ecological systems [26,69]. Therefore, ESs generated by ecological processes of agricultural systems should be understood as inextricably linked and co-evolving with agricultural practices [26,70]. It should be noted that the perceptions of farmers regarding how their agricultural practices affect the diverse provisioning and non-provisioning ESs they manage must be understood [71]. The perception is developed based on an individual's interaction with the environment, and particularly is influenced by both personal and external views and attitudes [72,73]. There are evidences to indicate that farmers have a direct interest in managing ESs such as soil fertility, pollination, pest control and maintenance of diversity, and especially for the high-income farmers [28,74]. However, the results suggest that a growth in annual household income will be associated with a higher impairment rate of the delivery of agricultural ESs. This further shows that gaps exist between the expression of attitudes toward ESs and the actual behavior performed by the farmers [75]. Thus, in terms of tackling the restoration of ESs and simultaneously increasing farmers' income, the government needs to promote significant changes in agricultural practices and policies to support agroecosystems upgrading.

4.2. Explanations of spatial effect of agricultural ESs

Agricultural IES is positive spatial dependence, which is not only related to complex natural capital in agroecosystems but also associated with farmers' decision making for agricultural management. Agricultural ESs are more closely connected and impacted by materials, energies and information flows from the neighboring regions in cross-regional collaborative governance and differentiated policy making. Indeed, the turning point would happen later with spatial effect considered, which expects that successful management actions will have to be coordinated across adjoining region. Therefore, formulating and implementing solutions to counteract agricultural ESs degeneration should not only focus on individual local village but also strengthen cooperation across neighboring villages.

The direct effects estimate of characteristic variables indicate that the local *EDU* and *VCFM* have significantly positive impacts on local agricultural ESs, while local *CLA* has significantly negative impacts on local agricultural ESs. Specifically, formal education could increase cognitive abilities, improving the perception of surroundings, affecting the ability to comprehend existent relations among ESs, recognizing their direct impact on agricultural production, and encouraging farmers to consciously improve the invisible ESs of agroecosystems, such as supporting services [30,57,73]. Therefore, in contexts where farmers have the less formal education, it is necessary to prioritize educational initiatives, such as environmental education or extension projects, that can help farmers develop more thinking and observation of natural processes to improve invisible ESs for local agroecosystems, especially village level. Consistent with previous studies suggesting that field margin vegetation in agroecosystems could provide a range of ESs, such as maintenance of natural genetic diversity and maintenance of semi-natural habitat [64,76], additionally our analysis points to that an increase in vegetative cover of field margin may help reduce erosion, runoff and agrochemical drift to benefit water purification. Thus, vegetative field margins, especially at the village scale, have potential as local invisible ESs sites to promote agroecosystem health as a prerequisite for sustainable agricultural development. There is a strong negative correlation between farm size and on-farm landscape heterogeneity for farms [77], especially the small-scale farms are associated with more varied landscapes and semi-natural habitats [78], so an increase in cultivated land area could lead to landscape homogenization and simplification, with negative implications for agricultural non-provisioning ESs. However, consolidation of large-scale farms would contribute to reduction in total nitrogen input and ammonia emissions and increase in nitrogen use efficiency [60,79]. Additionally, the production-living-ecological space of village scale would be mutually reinforced and restricted by establishing large-scale farms [80]. Overall, an increase in the area of cultivated land is a double-edged sword for eco-environmental development of agriculture. Accordingly, before implementation of rural land consolidation, field size increase should comprehensively consider the socio-economic aspects of its contribution and the ecological environment of its positive and negative effects.

The indirect effects estimate of characteristic variable indicate that the local *PC* has significantly positive impacts on agricultural ESs of neighboring villages. In other words, perennial crops can provide multiple ESs essential for sustainable production more effectively than annual crops, such as biological pest control, water purification, and maintenance of semi-natural habitat. For example, it has been shown that perennial crops might fulfil complementary roles to semi-natural habitats, not least for ground beetle diversity in agricultural landscapes to enhance biological pest control services [81]. Furthermore, it has also been demonstrated that perennial monocultures for foods (being unsuited to the environment or replacing forest cover) may cause environmental harms of local regions despite being perennial crops [82]. To further strengthen the favourable role of perennial crops for agricultural environment, therefore, it seems essential to focus not only on local environmental and managerial adaptations of perennial crops, but also on the provision of associated ESs from perennial crops in agricultural landscapes based on the spillover effect brought by the inter-relationship among regions.

4.3. Policy implications and recommendations

Based on the results and discussions above, three aspects of policy implications could be extracted to promote the sustainable development of agriculture:

Innovate and refine agro-ecological compensation mechanism to promote coordinated development of farmland space among neighboring villages. Agro-ecological compensation has attracted increasing interest as a mechanism in many countries around the world to encourage an effective combination agricultural environment protection with agrarian economies. It involves converting externalities of non-marketed ESs supplied by local households with willingness into practical financial incentives for them [28,83]. China has a "generalized system of preference" policy, which has been mainly composed of four subsidies: Direct Subsidy for Grain Farming, General Subsidy for Inputs, Subsidy for Growing Improved Varieties, and Subsidy for Purchasing Agricultural Machinery and Tools [84]. Contributing greatly to an increase in farmer income and grain production, these policies still brought environmentally unfriendly procedures. In December 2016, the State Council, Ministry of Finance (MOF) and Ministry of Agriculture (MOA) approved and jointly issued the Plan for Establishing Agricultural Subsidy Oriented to Green Ecology, which vigorously promote a green-ecology-oriented subsidy policy framework to improve the incentive measures for agricultural environment protection [84]. The results show that the turning point under the direct effect would happen earlier and under the indirect effect would happen later. In other words, with spatial effect considered, the influence of agrarian economy development on ESs undergo different stages. That is, local agrarian economy development is taken out at the cost of local ESs (the initial stage); and a growth agrarian economy in a certain village will be associated with not only a higher impairment rate of the delivery of ESs of that village but also relatively high levels of ESs harm within the surrounding villages (the advanced stage). Therefore, it is necessary to consider the spatial effect in the agro-ecological compensation mechanism design. According to different stages of the influence of agrarian economy development on ESs, the differential agro-ecological compensation payment criteria should be consequently regarded as innovative solutions to giving full play to the cooperation with the surrounding regions to promote coordinated development of farmland space among neighboring villages.

Strive for development of the diversified and coordinative land consolidation to avoid the single approach in practice. In China, croplands are village owned, which are allocated to one rural household through distribution across 3–5 different places to ensure a fair distribution of both high- and low-quality land for all households based on the household contract responsibility system [60]. As a result, the existence of land fragmentation in rural areas makes efficient management of croplands challenging. The original motivation of land consolidation (LC) is to improve managerial and economic efficiency by relieving the issue of land fragmentation and ameliorating rural infrastructure [85]. As agricultural environment gets more and more attention, the connotation of LC has gradually transformed to comprehensive benefits in socio-economic and environmental aspects. At present, maintaining food security is still one of the most critical tasks of practice in China's LC, while supporting environmental protection is just begins. The results indicate that local *CLA* and *VCFM* have significantly negative and positive impacts on local agricultural ESs, and local *PC* has significantly positive impacts on agricultural ESs of neighboring villages. That is, a set of measures for sustainable LC of comprehensive benefits should be adopted. One type of these measures aims at the balance of the socio-economic aspects of land use and its negative environmental effects (i.e., appropriate increases of field size) and another aims at promoting positive environmental effects and its spillovers (i.e., growing vegetation in the margin of the field, and generating positive spatial spillovers of multi-ESs from perennial crops). Thus, LC should integrate the conversion to appropriate large-scale farming with other environmental conservation measures to promote the use of farmland to be more diversified and coordinated.

Strengthen the publicity and education of agro-environmental protection to enhance the farmers' awareness of the effective use of farmland resource. The results show that the average length of formal education for the farmers in the study area is 7.14 years. Furthermore, the local *EDU* has significantly positive impacts on local agricultural ESs. In contexts where farmers have little schooling, it is necessary to strengthen the publicity and education of agro-environmental protection, helping farmers to perceive the ESs as essential to agriculture and human well-being [30,57]. On the one hand, the government must guide farmers to participate more technical training and to understand information orientation for agricultural policies. In this way, it enhances farmers' awareness of the importance of the agricultural policies and increases the efficiency of these policies (such as the agro-ecological compensation and land consolidation). On the other hand, the government can understand the benefit and priorities that farmers would consider through the publicity and education of agro-environmental protection. In the meanwhile, the agricultural policies can be modified by the combination of top-down and bottom-up approaches to support those benefit and priorities. Taken together, measures of the publicity and education can be a force for overcoming educational constraints, so that the farmers' benefit and priorities would be reflected in agricultural policies, which improve the efficiency of farmland use.

This paper puts forward three aspects of policy recommendations (agro-ecological compensation mechanism, the diversified and coordinative land consolidation, and the publicity and education of agro-environmental protection). The findings also suggest stakeholders cannot necessarily expect any policy will enhance a hoped-for set of ESs at any specific cases. A sensible strategy would be for policy-makers to promulgate a suite of policies to improve multi-ESs, rather than to assume that one policy will work as catch-all solutions in support of agricultural sustainability.

5. Conclusions

This study estimates the existence of EKC for the agricultural ESs by incorporating the spatial factors. Some conclusions are extracted as follows:

There is a significant inverted U-shaped curve for agricultural ESs, not a U-shape. Based on gaps existence between the expression of attitudes toward ESs and the actual behavior performed by the farmers, the government should promote significant changes in agricultural practices and policies (such as agro-ecological compensation policies) to support the sustainability of agriculture and environmental health. It should not only focus on individual local village but also strengthen cooperation across neighboring villages to counteract agricultural ESs degeneration. The influence of household income on non-provisioning ESs in agroecosystems is divided into two stages (the initial and advanced stage), so differential compensation should also be designed for different stages. The results of characteristic variables indicate that the local EDU, VCFM and CLA have significantly positive, positive and negative impacts on local agricultural ESs, while local PC has significantly positive impacts on agricultural ESs of neighboring villages. Perennial crops in local village can provide multi-ESs to neighboring villages than annual crops. The scale of this study is only at the village level. If more practical policies are to be implemented, the research scale should be extended to the municipal or provincial scale. In addition, more social and economic variables should be considered in future studies, so as to better identify the factors affecting IES and provide more substantial basis for policy formulation. The research of this paper can provide reference for other countries that have the same situation with Chinese agriculture.

Author contribution statement

Yajuan Chen: conceived and designed the experiments, performed the experiments, analyzed and interpreted the data, contributed reagents, materials, analysis tools or data, wrote the paper; Yaofeng Yang: conceived and designed the experiments, performed the experiments, analyzed and interpreted the data, contributed reagents, materials, analysis tools or data, wrote the paper; Lan Fang: analyzed and interpreted the data, wrote the paper; Hongkun Zhao: contributed reagents, materials, analysis tools or data, wrote the paper; Zhenwei Yang: contributed reagents, materials, analysis tools or data, wrote the paper; Ling Chen: contributed reagents, materials, analysis tools or data, wrote the paper; Huyang Yu: contributed reagents, materials, analysis tools or data, wrote the paper.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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