Article

Identifying the Driving Factors of Food Nitrogen Footprint in China, 2000–2018: Econometric Analysis of Provincial Spatial Panel Data by the STIRPAT Model

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Abstract: This paper studies the EKC hypothesis and STIRPAT model. Based on the panel data of carbon emission intensity and other influencing factors of 30 provinces in China from 2000 to 2018, the spatial effect of per capita food nitrogen footprint (FNF) and the effect of different socio-economic factors in China were studied by using exploratory spatial data analysis and fixed effect spatial Durbin model for the first time. The results show that: (1) there is a spatial agglomeration effect and a positive spatial dependence relationship in China's provincial per capita FNF (FNFP), which verifies that the relationship between China's FNF and economy is in the early stage of EKC hypothesis curve. (2) The driving forces of China's FNF were explored, including Engel's coefficient of urban households (ECU), population density (PDEN), urbanization, nitrogen use efficiency (NUE) and technology. (3) The results show that there is a significant spatial spillover effect of FNFP. The ECU and NUE can reduce the regional FNFP, and can slow down the FNFP of surrounding provinces. (4) Policy makers need to formulate food nitrogen emission reduction policies from the food demand side, food consumption side and regional level.

Keywords: per capita food nitrogen footprint; EKC hypothesis; STIRPAT model; spatial effect

1. Introduction

Over the past decades, China's economy has been developing at an amazing speed and has been widely concerned. By 2020, China's GDP reached CNY 101.6 trillion, and its total economic volume has reached a new level of CNY 1 trillion [1]. The gap between urban and rural development continues to narrow, the income growth of rural residents is faster than that of urban residents, and the urbanization exceeds 60% [1]. The rapid growth of the economy and the acceleration of urbanization are accompanied by the trend characteristics of high nutrition, high protein, and diversification in food consumption of residents [2]. The dietary structure of residents has changed from plant-based food consumption to animal and plant-based food, a staple food consumption, to non-staple food [2–4]. The process of food consumption and production is both sides of the relationship between social supply and demand, independent of each other, but also an organic whole. The choice of food consumption directly determines the input and output of nitrogen in the process of food production, and food consumption is the main driving force of food production [5]. As the basis element of maintaining agricultural production, nitrogen plays an irreplaceable role in green agricultural development [6]. However, excessive accumulation of reactive nitrogen in the environment will cause a series of negative effects on human health and ecosystem [7]. The European nitrogen assessment identified five major threats to nitrogen pollution: water quality, air quality, greenhouse gas balance, ecosystem and biodiversity, and soil quality [8]. These impacts impede the progress towards sustainable development goals because they affect human health, resource management,

livelihoods and the economy [9–13]. In recent years, nitrogen pollution management methods have changed [14], including new ideas of consumption and production, in order to seriously solve the problem of nitrogen [15–23]. Existing studies have shown that the loss of reactive nitrogen from food production and consumption is the most important factor causing China's nitrogen footprint, which has become one of the major environmental problems facing China [24]. In order to keep within limits man-made nitrogen emissions, realize the sustainable development of ecological environment and human health, it is very important to reveal the driving factors of nitrogen emissions.

In the field of environmental economics, there is abundant literature on the relationship between economic development and environmental quality, which can be better understood by means of EKC and STIRPAT which is a stochastic regression model for measuring the impact of population, affluence and technological changes on the environment. EKC Hypothesis is an important theory of empirical research on the relationship between economic growth and environment [25,26]. Since Grossman and Krueger (1991) [27] initiated this work, EKC Hypothesis revealed that the relationship between environmental deterioration and per capita income is an inverted U-shape, and the EKC Hypothesis has aroused great attention. Panayotou (1993) [28] confirmed the validity of the EKC Hypothesis. At present, the EKC Hypothesis, as a classical environmental economic theory, is widely used in the study of carbon emissions [29–31].

On the other hand, the STIRPAT model [32–34] is one of the most famous models in the literature of environmental economics. It is a mathematical generalization of the traditional IPAT (Impact = Population + Affluence + Technology) model proposed by Ehrlich and Holden (1971) [35]. It is a random version derived from the IPAT model. It overcomes the shortcomings of the assumption that the fixed proportion of environmental factors changes in the IPAT theoretical model [36]. The main goal of STIRPAT model is to estimate the impact of driving forces on ecology [37], to predict the non-proportional and non-monotonic functional relationships among the factors affecting the ecosystem [34,38], and to explain the driving forces of SO₂ [39], carbon dioxide (CO₂) [40] and PM_{2.5} [41], and other pollutant emissions. The advantage of the STIRPAT model is that it can evaluate the effect of driving factors [34], estimate the coefficient of each variable, and modify the influencing factors [42]. This model studies the effects of population, affluence and technology on carbon dioxide emission level [43,44]. Different scholars extended the STIRPAT model to incorporate additional factors into the traditional STIRPAT environmental impact model, enabling the extended STIRPAT model to study the impact of urbanization [45], industrial structure [46], trade openness [47] on greenhouse gas emissions, and other environmental consequences, which provides policy basis for energy conservation and emission reduction. When discussing the feasibility of EKC model, the literature is relatively rich. Due to the space problem, this paper only summarizes the different studies of nitrogen oxide (NO_x) EKC in nitrogen emissions, in addition, discusses the research progress of random influence EKC based on STIRPAT theory.

Table 1 shows the review of different studies on NO_x EKC, which is summarized from literature, country, time frame, research methods, variables and conclusions. Among the environmental indicators used in EKC research internationally, CO₂ emissions are still the preferred indicators, because it is the most common in empirical literature [48]. Nevertheless, the use of NO_x as a pollution indicator [28,49–56] has been recorded in earlier and recent literatures, even though it is slightly reduced compared with CO₂.

Table 1. A review of recent studies validating/invalidating the EKC hypothesis for NOx emission.

References	Country	Time Frame	Methodology	Variables Used	Conclusions
Hassan and Nosheen (2019) [50]	37 high-income nations	1990–2017	Panel unit root test Panel cointegration Panel GMM quadratic regression	Environment variable: CO ₂ , N ₂ O, CH ₄ Explanatory variables: GDP, FDI, RPC ^a , RGT ^b , ED ^c , TOP ^d , PG ^e	CO ₂ , CH ₄ : U shape; N ₂ O: inverted U shape
Luo, Chen, Zhu, et al. (2014) [51]	China	2003–2012	quadratic regression	Environment variable: PM ₁₀ , SO ₂ , NO ₂ , API Explanatory variables: GRP, POP ^f , IND ^g	NO ₂ : Inverted U shape
Brajer, Mead, Xiao (2011) [52]	China	1990–2006	random-effects GLS, quadratic and cubic regression	Environment variable: SO ₂ , TSP, NO ₂ Explanatory variables: PC ^h , POP	Inverted U shape
Hill and Magnani. (2002) [53]	A total of 156 countries	1975–1995	GLS, Cross-section analysis, quadratic and cubic regression	Environment variable: CO ₂ , SO ₂ , N ₂ O Explanatory variables: GDP	Inverted U shape, N-shaped
Cho, Chu, Yang (2014) [54]	A total of 22 OECD countries	1971–2000	Panel unit root, Panel cointegration tests, FMOLS, quadratic regression	Environment variable: CO ₂ , CH ₄ , N ₂ O Explanatory variables: GDP, ENRG ⁱ	Inverted U shape
Giovanis (2013) [55]	British	1991–2009	FE, Arellano-Bond GMM, logit, quadratic regression	Environment variable: O ₃ , SO ₂ and NO _x Explanatory variables: PC	Inverted U shape
Liddle (2015) [56]	A total of 84 cities in both developed and developing countries	1995	OLS, quadratic regression	Environment variable: CO, NO _x , VHC Explanatory variables: GDP, URB, FP ^j	Inverted U shape
Gao and Zhang (2019) [57]	18 Mediterranean countries	1995–2010	Panel unit root tests, Panel cointegration tests, FMOLS, Panel Granger causality tests quadratic regression	Environment variable: CO ₂ , CO, NO _x , SO ₂ , PM _{2.5} , PM ₁₀ Explanatory variables: GDP, ENE ^k , TOUR ^l	CO ₂ , CO, NO _x , SO ₂ , PM _{2.5} , PM ₁₀ : inverted U shape in northern panel; CO, SO ₂ , PM _{2.5} , PM ₁₀ : inverted U shape in Southern panel
Roca, Padilla, Farré, et al. (2001) [58]	Spain	1980–1996	OLS	Environment variable: CO ₂ , SO ₂ , NO _x , CH ₄ , N ₂ O, NMVOC Explanatory variables: GDP	SO ₂ : inverted U shape CO ₂ , NO _x , CH ₄ , N ₂ O, NMVOC: EKC hypothesis not confirmed
Miah, Masum, Koike (2010) [59]	Bangladesh	2008.08–2009.08	Reviewing the available literature	CO ₂ , SO _x , NO _x	SO _x , NO _x : inverted U shape; CO ₂ : EKC hypothesis not confirmed
Haider, Bashir, Husnainc (2020) [60]	Top 15 countries ranked by N ₂ O emissions, top 18 countries ranked by agricultural share of GDP	1980–2012	Panel unit root, Panel co-integration, Cross-section dependence test, PMG and MG estimators, Dynamic panel causality, quadratic regression	Environment variable: N ₂ O, N ₂ OA ^m Explanatory variables: GDP, ALU ⁿ , EXP ^o	Inverted U shape
Xu, Li, Miao, et al. (2019) [61]	China	2005–2015	Expanded STIRPAT, quadratic and cubic regression	Environment variable: SO ₂ , NO _x , PM _{2.5} Explanatory variables: GDP, EX ^p , FDI, IND, R&D, URB, POP	Inverse N shape in eastern and western region; Inverted U shape in central region
Och (2017) [48]	Mongolia	1981–2012	Cointegration analysis, Granger causality, VECM, quadratic regression	Environment variable: NO _x Explanatory variables: PC, PCsq ^q , EX, URB, AG, IND, and SER ^r	U shape

Table 1. Cont.

References	Country	Time Frame	Methodology	Variables Used	Conclusions
Fong, Salvo, Taylor (2020) [62]	Nine countries in Southeast Asia	1993–2012	Standard EKC, Spatial EKC, quadratic regression	Environment variable: NO _x , SO ₂ , PM _{2.5} Explanatory variables: GDP, UB, RE ^s , SV ^t , EI ^u , FDI	Inverted U shape
Wang, Yang, Wang, et al. (2017a) [63]	U.S.	CO ₂ : 1960–2010 N ₂ O: 1980–2009 CH ₄ : 1990–2009	Stationarity test, Co-integration test, regression tests	Environment variable: CO ₂ , N ₂ O, CH ₄ Explanatory variables: GDP	CO ₂ , N ₂ O: Wave shape CH ₄ : U shape
Zambrano-Monserrate and Fernandez (2017) [64]	Germany	1970–2012	OLS, ARDL, VECM-Granger, quadratic regression	Environment variable: N ₂ O Explanatory variables: GDP, ALU, EXP	Inverted U shape
Zhang, Sharp, Xu (2019a) [65]	China	2005–2015	EDSA, SLM, SDM, quadratic regression	Environment variable: NO _x , PM ₁₀ , VOCs, PM _{2.5} , SO ₂ Explanatory variables: GDP, ENE, IS ^v , FDI, TI ^w , FC ^x , R&D	NO _x , PM ₁₀ , VOCs, PM _{2.5} : Inverted U shape SO ₂ : EKC hypothesis not confirmed
Halkos and Polemis (2017) [66]	The 34 countries of OECD	1970–2014	Cross-Section Dependence, Unit Root and Cointegration Testing, MLE, FGLS, DIF-GMM, SYS-GMM, cubic regression	Environment variable: CO ₂ , NO _x Explanatory variables: GDP, CREDIT, STOCK, BOND ^y	N shape
Fujii and Managi (2016) [67]	A total of 38 countries	1995–2009	FE, GLS, quadratic and cubic regression	Environment variable: CO ₂ , CH ₄ , N ₂ O, NO _x , SO _x , CO, NMVOC, NH ₃ Explanatory variables: GDP	CO ₂ , CH ₄ , N ₂ O, NMVOC, NH ₃ : Inverted U shape; NO _x , SO _x : inverse N shape
Sinha and Bhatt (2017) [68]	India	CO ₂ : 1960–2011 NO _x : 1970–2012	Augmented Dickey Fuller test, cubic regression	Environment variable: CO ₂ , NO _x Explanatory variables: GDP	N shape
Rasli, Qureshi, Isah-Chikaji, et al. (2018) [69]	A total of 36 developed and developing countries	1995–2013	Panel robust least square MM-regression, quadratic regression	Environment variable: N ₂ O, CO, CO ₂ , SO ₂ , NO _x Explanatory variables: GDP, IND, TOP, ENRG, PCFPROD ^z	N ₂ O, CO: Inverted U shape
Ge, Zhou, Zhou, et al. (2018) [70]	China	2010–2015	STIRPAT, SDM, LM	Environment variable: NO _x Explanatory variables: GDP, URB, POP, EI	Inverse N shape
Selden and Song (1994) [71]	A total of 22 OECD and 8 developing countries	1979–1987	Quadratic, RE	Environment variable: TSP, SO ₂ , NO _x , CO Explanatory variables: GDP	Inverted U shape
Panayotou (1993) [28]	A total of 68 developed and developing countries	1988	OLS, quadratic regression	Environment variable: SO ₂ , NO _x , SPM Explanatory variables: PC, POP	Inverted U shape

Note is ^a. RPC is Railways Passenger Carriage; ^b. RGT is Railways Goods Transported; ^c. ED is Energy Demand; ^d. TOP is Trade Openness; ^e. PG is Population Growth; ^f. POP is population size; ^g. IND is secondary industry sector; ^h. PC is per capita income; ⁱ. ENRG is energy use; ^j. FP: fuel price; ^k. ENE is energy consumption; ^l. TOUR is tourism receipts; ^m. N₂OA is agricultural N₂O emissions; ⁿ. ALU is agricultural land use; ^o. EXP is exports of goods and services; ^p. EX is exports; ^q. PCsq is the square of per capita income; ^r. AG, IND, and SER are agricultural, industrial, and services value added, respectively; ^s. RE is renewable energy; ^t. SV is Share of services sector; ^u. EI is Primary energy intensity; ^v. IS is secondary industry value-added; ^w. TI is civilian vehicles; ^x. FC is Forest coverage; ^y. BOND is corporate bond issuance volume; ^z. PCFPROD is food production variability.

The EKC hypothesis of NO_x has been studied in OECD [54,66,71], Asia [48,68,70], Europe [55,57,58,64], America [63], developing countries, and developed countries [28,56,69], and most of them have been verified.

In addition to the OLS regression model [28,56,58] commonly used in NO_x EKC hypothesis research, the unit root test and cointegration test [50,54,57,60,66,68] are generally used in the statistical sample data. With the development of econometric research, the vector error correction model (VECM) [48,64], generalized moment estimation (GMM) [50,55,66], fully modified least squares method (FMOLS) [54,57], generalized least squares estimator (GLS) [52,53,67], cross-section dependence test [53,60,66], co-integration autoregressive distribution lag (ARDL) [64] boundary test methods are all popular in the research of NO_x EKC hypothesis.

Similarly, many influencing variables of NO_x emission have been identified. GDP per capita income is still the most widely used economic indicator to date, followed by per capita income [48,52,55]. Export [48,60,64], urbanization [48,56,61,62,70], foreign direct investment [50,61,62,65], and industrial structure [48,51,61,69] have been widely studied as influential variables in the research model, and are considered to have a significant impact on the relationship between NO_x emissions and economic growth. The research conclusions reflect that most of the NO_x emissions and the economy/income are in an inverted U-shape or an inverted N shape, which verifies the existence of EKC.

Based on the STIRPAT theory framework and EKC hypothesis, the current research mainly focuses on the following fields: The impact of income on carbon emissions in the African continent [72], the determinants of CO₂ emissions in Tianjin [73], the decoupling of the income–environment dynamic relationship between CO₂ and air pollutants at the Italian sector level [74], the driving factors of CO₂ emissions in high-, middle- and low-income countries [75], the impact of Australia's main driving forces on the environment [76], the determinants of CO₂ emissions in Chinese cities [77], the driving forces of energy-related CO₂ emissions in China [78], the impact of human driving forces on the ecological footprint of Gannan Pastoral Area [79], and the impact of international trade on CO₂ emissions [80], etc. There are also few literatures based on the combination of STIRPAT and EKC to study the impact of urbanization [70], exports and foreign direct investment [61] on NO_x emissions. The results of the study confirmed the existence of EKC within the framework of STIRPAT.

Nowadays, it is rare to conduct research on NO_x EKC hypothesis from a spatial econometrics perspective [65,70] of available literature. Spatial effect is the key factor to evaluate the impact of economic development on environmental conditions [81,82], and the spatial correlation of data is the inherent feature of many environmental disciplines [70]. EKC finally presents the uncertainty results such as positive linear relationship, inverted U-shaped relationship, U-shaped relationship, N-shaped relationship, and no relationship [62]. When there is a spatial relationship, ignoring the spatial control in the econometric model will lead to biased estimation [83,84]. The impact of NO_x is more local or regional than other pollutants in the world. It can be expected that it will be one of the pollutants more likely to be realized by EKC hypothesis [58]. One direction of future research may be to include spatial aspect (i.e., geographical proximity), so as to reveal possible regional differences and the sources of different EKC models [66].

Many literatures have adopted different environmental deterioration variables. The environmental variables listed in Table 1 above are mainly single substance pollutants, such as CO₂, SO₂, CH₄ and N₂O, discuss the relationship between environmental deterioration and socio-economic development. The use of a single substance pollutant measurement indicator will cause errors in the measurement results due to insufficient comprehensiveness [85]. In fact, the overall concept of pollution is composed of different components. The performance of these components may be different, and it is not easy to merge into a single measurement standard [52]. The standard can be used for reference to the construction method of the Comprehensive Environmental Index (CEI) [86]. This study uses FNF as an environmental quality indicator. Based on the EKC model and STIRPAT model, this study

uses the FNF as an environmental quality indicator, and selects the panel data of the FNF and related regional development factors of 30 provinces in China from 2000 to 2018 to make empirical estimation through spatial econometric models, then analyzes whether there is a spatial autocorrelation relationship between FNFs in various regions of China, and estimates the spatial spillover effects of various factors by establishing a spatial panel model of FNF and each influential factor.

2. Model, Methodology, and Data

2.1. Calculation of Food Nitrogen Footprint

According to the definition of NF proposed by Leach et al. (2012) [87], FNF in this study can be divided into food consumption nitrogen footprint (FCNF) and food production nitrogen footprint (FPNF). The calculation method of FPNF and FCNF is based on the adjusted version of N-calculator. FNF reflects the sum of N losses associated with food production and food consumption. FPNF refers to the loss of all N from food production to food consumption. FCNF refers to the amount of food nitrogen consumed by human beings, assuming that the nitrogen excreted by adults is the same as that in food described by Leach et al. (2012) [87].

The FNF_{PC} is calculated according to the following formula:

$$FNF_{PC} = \sum_{i=1}^n (FCNF_i + FPNF_i) \quad (1)$$

In Equation (1), FNF_{PC} is the FNF, $FCNF_i$ is the per capita FCNF of item i food, $FPNF_i$ is the per capita FPNF of item i food, and i refers to all kinds of food ($n = 8$).

2.1.1. FCNF Calculation

The per capita FCNF is calculated by the following formula:

$$FCNF_{PC} = \sum_{i=1}^n (C_i \times N_i) \quad (2)$$

In Equation (2), $FCNF_{PC}$ is the per capita FCNF, C_i is the per capita food consumption of item i food, and N_i is the nitrogen content of item i food.

In order to estimate FCNF, we assume that nitrogen does not accumulate in the human body, which means that all consumed nitrogen is lost in the sewage flow [87]. Due to the lack of available data on the effectiveness or any temporal variation of nitrogen removal from wastewater treatment plants, this study did not consider wastewater treatment using nitrogen removal technology [88], and all nitrogen consumed by human beings was released into the environment in the form of human waste. The level of nitrogen content of different foods is found by multiplying the food protein content by the conversion coefficient of 0.16 [87]. The nitrogen content of 8 items of different foods is shown in Table 2 [4,89–91].

Table 2. Nitrogen content and virtual N factors in different food items.

Food Item	Virtual Nitrogen Factor	Nitrogen Content (g/kg)
Cereal	1.4	14.4
Vegetable	10.6	1.76
Fruit	10.6	1.6
Livestock meat	4.7	29.22
Poultry meat	3.4	29.9
Aquatic product	3	28.77
Egg	3.4	20.48
Dairy	5.7	5.28

2.1.2. FPNF Calculation

Virtual Nitrogen Factor (VNF) is introduced into the NF accounting of food production. VF refers to any nitrogen produced in the process of food production that will not be directly

consumed by human beings, including all nitrogen lost by nitrogen fertilizer application in farmland, livestock breeding and food processing [87]. In order to define the boundary and avoid repeated calculation, in the calculation of VF, the nitrogen loss caused by energy consumption in food production is generally excluded, and this part of nitrogen loss is calculated into the energy NF. VNFs are calculated by dividing total nitrogen loss by total available nitrogen. The per capita FPNF is calculated as follows:

$$FPNF_{PC} = \sum_{i=1}^n (FCNF_i \times VNF_i) \quad (3)$$

In Equation (3), $FPNF_{PC}$ is the per capita FPNF, and VNF_i is the VNF of food item i .

We determined the VNF in this study based on regional characteristics, the time span, main food consumption, and data availability (Table 2).

2.2. Environmental Kuznets Curve Hypothesis

EKC was originally an empirical hypothesis, which described an inverted U-shaped curve between economic development and environmental quality. Various indicators of environmental quality degraded with economic growth at the initial stage, and after reaching the threshold stage, environmental degradation began to decrease [25]. Since the EKC hypothesis is based on the relative importance of scale effect, composition effect, and technique effect, structural modeling should be performed to identify them. However, some simplified models have been used to test the validity of EKC hypotheses in empirical literature. The following general simplified model is used to test the EKC hypothesis in the empirical literature [92].

$$Y_{it} = \alpha_i + \beta_1 X_{it} + \beta_2 X_{it}^2 + \beta_3 Z_{it} + e_{it} \quad (4)$$

i : 1, 2, ..., 30 provinces

t : 2000, 2001, ..., 2018 year

In Equation (4), Y is the dependent variable representing environmental pollutants, X is the independent variable used as an economic income indicator, Z is the vector of other control variables that can affect Y , α is the intercept, β_i is the estimated regression coefficient, and e is the error term. In this paper, the environmental pressure dependent variable Y is measured by FNFP, and the economic output variable X is measured by GDPP. Many studies use the logarithmic form of the simplified model described above [60,93–96]. Select the most appropriate function form for the data and have a higher explanatory power within the data range [97]. The significance of model parameter β_i is estimated and tested. Dinda (2004) [92] pointed out that the following five results may occur:

- i. If $\beta_1 = \beta_2 = 0$, then there is no relationship between Y and X .
- ii. If $\beta_1 > 0$ and $\beta_2 = 0$, then there is a monotonic increasing or linear relationship between Y and X .
- iii. If $\beta_1 < 0$ and $\beta_2 = 0$, then there is a monotonic decreasing relationship between Y and X .
- iv. If $\beta_1 > 0$, $\beta_2 < 0$, then there is an inverted U-shaped relationship between Y and X , thus, the EKC hypothesis is valid.
- v. If $\beta_1 < 0$, $\beta_2 > 0$, then there is a U-shaped relationship between Y and X .

2.3. The Extended STRIPAT Model

The STRIPAT model is used as the theoretical basis of this study. Firstly, it is used to verify the existence of EKC between GDPP and FNFP, and secondly, to estimate the driving factors of per capita FNF in China. As a model widely used in ecological environment research, the main idea of STRIPAT is that environmental impact is a function of Population

(P), Affluence (A), and Technology (T). The stochastic form of STIRPAT modified by Dietz and Rose [34], which is expressed as follows:

$$I_i = \alpha P_i^b A_i^c T_i^d \varepsilon_i \quad (5)$$

Given this, we establish the following panel data model:

$$\ln I_{it} = \alpha_i + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + \varepsilon_{it} \quad (6)$$

i : 1, 2, ..., 30 provinces

t : 2000, 2001, ..., 2018 year

In Equation (6), I is the environmental impact, and the FNFP is selected to measure the environmental impact, the PDEN is selected to represent the population P , the GDPP is selected to represent the affluence A , the ratio of the number of patent applications to the total population is selected to represent the technology T . b , c and d are the elastic coefficients of $\ln P$, $\ln A$ and $\ln T$, respectively. α is a constant term, and ε is an error term.

Through logarithmic transformation of the variables in Equation (4), a logarithmic regression form for estimating and testing hypotheses is obtained. Combining with Equation (6), we deduce the existence verification model of EKC under the framework of STIRPAT model, which is expressed as follows:

$$\ln I_{it} = \alpha_i + b_1 \ln P_{it} + b_2 (\ln P_{it})^2 + c \ln A_{it} + d \ln T_{it} + \varepsilon_{it} \quad (7)$$

In order to achieve the research purpose, it is necessary to consider many driving factors that affect the FNFP as independent variables. Based on the explanation in Table 1, this paper constructs an empirical model after the extended STIRPAT model, as shown in Equation (8). Table 3 summarizes the selection, interpretation, and description of variables.

$$\begin{aligned} \ln FNFP_{it} = & \beta_0 + \beta_1 \ln GDPP_{it} + \beta_2 (\ln GDPP_{it})^2 + \beta_3 \ln PDEN_{it} \\ & + \beta_4 \ln TECH_{it} + \beta_5 \ln OPEN_{it} + \beta_6 \ln URB_{it} \\ & + \beta_7 \ln POPI_{it} + \beta_8 \ln NUE_{it} + \beta_9 \ln ECU_{it} + \varepsilon_{it} \end{aligned} \quad (8)$$

Table 3. Variable explanation and instruction.

Variable Type	Variable Explanation	Unit
Explained variable		
Per capita Food Nitrogen Footprint (FNFP)		Kg/person
Explanatory variable		
Per capita GDP (GDPP)	Ratio of GDP to total population	CNY 10,000 RMB/person
Population Density (PDEN)	Ratio of resident population to land area	Person/km ²
Technology (TECH)	Ratio of patent applications to total population	Pieces/10,000 people
Openness (OPEN)	Ratio of total import and export to GDP	-
Urbanization (URB)	Ratio of urban population to total population	%
Industrial Structure (POPI)	The ratio of the output value of the primary industry to the regional GDP	%
Nitrogen Use Efficiency (NUE)	Ratio of total grain yield to nitrogen fertilizer application	Kg/kg
Engel Coefficient of Urban Households (ECU)	Proportion of total food expenditure of urban households in total consumption expenditure	%

2.4. Exploratory Spatial Data Analysis

2.4.1. Global Spatial Autocorrelation Analysis

The global Moran's I index can be used to measure the spatial distribution pattern of FNF and to test the spatial autocorrelation of FNF in China. The calculation formula of global Moran's I index is as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (9)$$

In Equation (9), I is the global Moran index; x_i and x_j are the FNF_{PC} of the i and j provincial spatial units respectively; n is the number of selected provincial units; $\bar{x}$ is the mean value of FNF_{PC} ; W_{ij} is the spatial weight matrix. This study adopts 3 forms: adjacency weight matrix, geological distance weight matrix, and economic distance weight matrix.

2.4.2. Local Spatial Autocorrelation

Local Moran's I index indicates whether there is a high-value or low-value concentration of FNF and its neighboring provinces. The local Moran's I index is calculated as follows:

$$I_i = \frac{(x_i - \bar{x})}{S^2} \sum_{j=1}^n W_{ij} (x_j - \bar{x}) \quad (10)$$

In Equation (9), S is the standard deviation of FNF_{PC} of each province; x_i , x_j , n , $\bar{x}$, W_{ij} have the same meaning as x_i , x_j , n , $\bar{x}$, W_{ij} in global spatial autocorrelation analysis Equation (9).

2.5. Spatial Panel Econometric Model

If exploratory spatial data analysis does find the spatial autocorrelation of the data, spatial econometric analysis should be used. Spatial econometric analysis was first proposed by Anselin (1988) [83]. The model in this study is based on the spatial panel data model proposed by Elhorst (2015) [98], which combines the advantages of spatial model and panel data model, and considers the spatial effect of driving factors of FNF.

Generally speaking, there are three spatial panel data models [99]: spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM). The general form of these spatial panel data models [98] is as follows:

$$Y_t = \rho WY_t + X_t\beta + WX_t\theta + \mu + \xi_t\epsilon_N + u_t, \\ u_t = \lambda Wu_t + \varepsilon_t \quad (11)$$

Based on the empirical model of extended STIRPAT (Equation (8)) and the general form of spatial panel data model (Equation (11)), the spatial Durbin panel model of this study is constructed. The specific expression (Equation (12)) is as follows:

$$\begin{aligned} \ln NFP_{it} = & \rho W \ln NFP_{it} + \beta_1 \ln GDPP_{it} + \beta_2 (\ln GDPP_{it})^2 + \beta_3 \ln PDEN_{it} \\ & + \beta_4 \ln TECH_{it} + \beta_5 \ln OPEN_{it} + \beta_6 \ln URB_{it} + \beta_7 \ln POPI_{it} \\ & + \beta_8 \ln NUE_{it} + \beta_9 \ln ECU_{it} + \theta_1 W \ln GDPP_{it} + \theta_2 W (\ln GDPP_{it})^2 \\ & + \theta_3 W \ln PDEN_{it} + \theta_4 W \ln TECH_{it} + \theta_5 W \ln OPEN_{it} + \theta_6 W \ln URB_{it} \\ & + \theta_7 W \ln POPI_{it} + \theta_8 W \ln NUE_{it} + \theta_9 W \ln ECU_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \end{aligned} \quad (12)$$

In Equation (12), W is a standardized non-negative spatial weighting matrix, which represents the adjacency relationship between regions. ρ is the regression coefficient of the dependent variable on the spatial autocorrelation, which indicates the impact of provincial FNF on other provinces. θ is the coefficient of the spatial lag term of the independent

variable, which represents the spatial spillover effect of the independent variable on neighboring provinces. The more significant θ is, the stronger the spatial interaction of the independent variables is. β is used to measure the effect of independent variables on the change of FNF in the province. α_i and γ_t are spatial and time fixed effects, respectively, and ε is an unobservable random error.

In Equation (12), when θ is equal to 0, The model is Spatial Lag Model (SLM). SLM only contains the spatial lagged term of the dependent variable, which is expressed as:

$$\begin{aligned} \ln NFP_{it} = & \rho W \ln NFP_{it} + \beta_1 \ln GDPP_{it} + \beta_2 (\ln GDPP_{it})^2 + \beta_3 \ln PDEN_{it} \\ & + \beta_4 \ln TECH_{it} + \beta_5 \ln OPEN_{it} + \beta_6 \ln URB_{it} + \beta_7 \ln POPI_{it} \\ & + \beta_8 \ln NUE_{it} + \beta_9 \ln ECU_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \end{aligned} \quad (13)$$

In Equation (12), when θ is equal to $-\rho\beta$, the model is the Spatial Error Model (SEM). SEM only contains the spatial dependence of random errors, which is expressed as:

$$\begin{aligned} \ln NFP_{it} = & \beta_1 \ln GDPP_{it} + \beta_2 (\ln GDPP_{it})^2 + \beta_3 \ln PDEN_{it} \\ & + \beta_4 \ln TECH_{it} + \beta_5 \ln OPEN_{it} + \beta_6 \ln URB_{it} \\ & + \beta_7 \ln POPI_{it} + \beta_8 \ln NUE_{it} + \beta_9 \ln ECU_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \\ \varepsilon_{it} = & \lambda W \varepsilon_{it} + \mu \end{aligned} \quad (14)$$

2.6. Test of Spatial Panel Model

In estimating, spatial econometric models need to be screened using appropriate methods and procedures, mainly using LM tests and (Robust) LM tests to test whether spatial factors are included, and to establish a spatial model. Then which form of spatial panel model is adopted by Wald and LR tests [100]. In the process of a test, the following criteria can be selected:

According to the selection conditions of SLM and SEM established by Anselin et al. (2008) [101], the corresponding OLS model is established for panel data, and the residual items are analyzed and judged by LM test and (Robust) LM test, and the form of the model is determined according to the significant level of the Lagrangian Multiplier contained in the LM and Robust LM tests. If the Lagrangian multiplier of the lag model is more significant than that of the error model, and the Robust-LMLag of the lagged model is significant, but the Robust-LMError of the error model is not significant, the SLM model is selected. If the Lagrangian multiplier of the error model is more significant than that of the lag model, and Robust-LMError of the error model is significant, but the Robust-LMLag of the lag model is not significant, the SEM model is selected.

Lesage and pace (2009) [84] believe that the loss caused by ignoring the hysteresis of error term itself will be less than the loss caused by ignoring the common spatial effect of independent variable and dependent variable. On this basis, Elhorst (2014) [102] proposed that SDM model should be given priority in model estimation, and at the same time, LR and Wald tests were used to consider whether SDM should be converted into SLM model or SEM model. The effects achieved by the LR and Wald tests are approximately equivalent. According to the above conversion conditions of spatial model, the null assumption of SDM conversion to SLM and SEM is expressed as: $\theta = 0$ and $\theta = -\rho\beta$. Under the LM test condition, if the model passes LR test or Wald test, H_0 is refused, then SDM model can be considered.

2.7. Data Sources

The data of FNF covering a period of 19 years, from 2000 to 2018, involving the per capita consumption data of 8 items food, including grain, vegetables, melons and fruits, animal meat, poultry meat, aquatic products, eggs and milk. Geographically, it covers 30 provinces in China. Due to data availability, this study does not include Tibet, Taiwan, Hong Kong, and Macao. Specific data sources: (1) urban per capita food consumption data.

The 8 items food data from 2015 to 2018 are from China Statistical Yearbook (2016–2019); the 8 items food data from 2013 to 2014 are from the survey yearbooks and statistical yearbooks of 30 provinces in the same year; the 8 items food data from 2000 to 2012 are calculated from the annual average per capita consumption expenditure of urban households in various regions and the consumer price sub index of each region, and the two kinds of data are from China Statistical Yearbook (2001–2013). (2) rural per capita food consumption data. The per capita consumption data of grain, vegetables, livestock meat, poultry meat, aquatic products, and eggs in 2000–2012 are from China Statistical Yearbook (2001–2013), and the per capita consumption data of melon, fruit, and milk are from China Rural Household Survey Yearbook (2001–2013); the 8 items of food data in 2013–2014 are from the survey Yearbook and statistical yearbook of 30 provinces in that year; and the 8 items food data in 2015–2018 are from China Rural Household Survey Yearbook (2001–2013). The data of per capita consumption of goods comes from China Statistical Yearbook (2016–2019).

The main data sources for this study are the output value of primary industry, GDP, the number of permanent residents, patent applications, total imports and exports, urbanization, per capita disposable income of urban residents, GDPP. These data are from China Statistical Yearbook (2001–2019). The data sources of nitrogen fertilizer application and total grain output are from China Rural Statistical Yearbook (2001–2019). ECU from China Statistical Abstract (2001–2019). The land area data of each province comes from *statistical table of administrative divisions of the people's Republic of China* [103]. Table 4 shows the descriptive statistical results of the main indicators used in this paper.

Table 4. Summary statistics.

Variable	Obs.	Mean	S.D.	Min.	Max.
lnNFP	570	2.64	0.15	2.23	2.99
lnGDPP	570	3.17	0.85	1.02	4.94
lnPDEN	570	5.42	1.26	1.98	8.24
lnTECH	570	1.29	1.49	−2.81	4.59
lnOPEN	570	2.89	0.98	0.56	5.16
lnURB	570	3.88	0.3	3.14	4.5
lnPOPI	570	2.27	0.85	−1.2	3.64
lnNUE	570	3.09	0.43	2.02	4.5
lnECU	570	3.55	0.15	2.99	3.9

3. Empirical Results

3.1. Spatial Distribution of Food Nitrogen Footprint in China

In order to explore the spatial effects of FNF in China, we calculated the spatial statistics of Moran's *I* across the region, represented by the Moran scatter diagram, with examples in 2000, 2010 and 2018. As shown in Figure 1, the Moran scatter plot shows the global Moran's *I*-index, *Z*-statistic, and *p*-value. The horizontal axis represents the FNF, and the vertical axis represents spatial lag of FNF. Each value represents the corresponding province of China. The points in the first quadrant H-H (High High) and the third quadrant L-L (Low Low) indicate that the FNF of the province and neighboring provinces are higher and lower, respectively. The points in the second quadrant L-H (Low High) and the fourth quadrant H-L (High Low) indicate that the FNF of the province is significantly lower and higher than that of adjacent provinces, respectively. The slope of the point regression line in the scatter plot is actually the value of Moran's *I*.

(a) 2000 year

(b) 2010 year

(c) 2018 year

Figure 1. Moran scatter plot of per capita food nitrogen footprint in China for 2000, 2010 and 2018.

It can be seen from Figure 1 that China's FNFP has a significant spatial dependence, with Moran's I index passing the 1% significance test in 2000 and 2010 and reaching the 5% significance level in 2018. The positive value of Moran's I reveals the positive spatial autocorrelation of FNFP. The higher Moran's I value, the more obvious the spatial correlation of FNFP. In addition, according to our calculations for all 19 years during the study period, the Moran's I values ranged from 0.138 to 0.351, and all values passed the 1% or 5% significance test, which indicates that the positive spatial autocorrelation has long-term stability [104].

3.2. Selection of Spatial Panel Model

Through the above exploratory spatial data analysis, the existence of spatial autocorrelation of FNFP was confirmed. In accordance with the steps proposed by (Elhorst, 2014a) [105], firstly, without considering the spatial effect, OLS was used to estimate the non-spatial model to test the relationship between economic growth and FNFP. Secondly, regarding panel data analysis, we examined four types of fixed effects: pooled OLS, spatial fixed effects, time fixed effects, and two-way fixed effects. According to the estimation results, the test of application space model is given in the results (Table 5).

Table 5. Estimation results of food nitrogen footprint EKC using panel data without spatial effect considered.

Variable	Pooled OLS	Spatial Fixed Effects	Time Fixed Effects	Two-Way Fixed Effects
Intercept	2.2343 *** (7.71)			
lnGDPP	−0.3457 *** (8.94)	−0.3208 *** (−3.79)	−0.2219 *** (−3.07)	−0.1723 (−1.39)
(lnGDPP) ²	0.0520 *** (8.16)	0.0456 *** (3.07)	0.0335 *** (3.39)	0.0267 ** (2.11)
lnPDEN	0.0269 * (1.53)	0.1030 (0.36)	0.0306 * (1.58)	0.1506 (0.53)
lnTECH	0.0236 ** (2.32)	0.0255 * (1.32)	−0.0019 (−0.12)	0.001 (0.06)
lnOPEN	−0.0078 (0.70)	−0.0134 (−0.45)	0.0085 (0.36)	0.0053 (0.23)
lnURB	0.1982 *** (3.35)	0.2089 ** (2.04)	0.0511 (0.52)	0.0354 (0.32)
lnPOPI	0.0428 ** (2.33)	0.0343 (0.79)	−0.0193 (−0.52)	−0.0117 (−0.23)
lnNUE	0.0060 (0.35)	0.0076 (0.16)	0.0279 (0.70)	0.0315 (0.71)
lnECU	−0.0268 (0.62)	−0.0407 (−0.41)	0.5582 *** (4.22)	0.5476 *** (4.57)
R ²	0.2140	0.8037	0.4011	0.2329
sigma ²	0.0142	0.0137	0.0066	0.0061
Durbin-Watson	0.2914	0.8849	0.5835	0.6051
loglikfe	408.4540	417.9207	625.6958	647.2188
LM test no spatial error	452.1147 ***	463.8650 ***	174.8818 ***	172.5474 ***
Robust LM test no spatial error	427.8300 ***	9.3641 ***	6.0178 **	6.8252 ***
LM test no spatial lag	24.9782 ***	520.8783 ***	173.0645 ***	170.5969 ***
Robust LM test no spatial lag	0.6935	57.2805 ***	4.2005 **	4.8747 **

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors z in parenthesis.

First of all, we tested the relationship between spatial error and spatial lag of panel data. In the absence of spatial factors, we used a Lagrange multiplier test for four models (pooled OLS, spatial fixed effects, time fixed effects, and two-way fixed effects) of ordinary panel data. The no-spatial error effect and no-spatial lag effect of LM and Robust LM were tested by the spatial toolkit provided by Elhorst (2014a) [105]. Results (Table 5) show that in the mixed OLS, spatial fixed, temporal fixed, and double fixed effects, the probabilities of the LM test no spatial lag are significant at 1% level except for Robust LM test no spatial error of time fixed effects with at 5%, and therefore four types of fixed refused the null hypothesis of no spatial error relationship of the model. The probability of the LM test with no spatial error is significant at the 1% level. Pooled OLS fails to pass the Robust LM test no spatial error, and the spatial fixed effects, time fixed effects and two-way fixed effects pass

the significant levels of 1%, 5% and 5% of Robust LM test no spatial lag, respectively. The goodness of fit of the pooled OLS, spatial fixed effects, time fixed effects and two-way fixed effects was compared from R^2 , the goodness of fit of spatial fixed effect model is greatly improved to 0.8037, which is far higher than the other three fixed effects with R^2 lower than 0.5.

Next, in the comparison of fixed effect model and random effect model, Hausman test results show that in the case of 9 degrees of freedom, the test value is 20.39, which passes the 5% significance level test and refuses the random effect model. Therefore, the spatial fixed effect model will be selected in this study.

Once again, in order to further test the fitting effect of SEM and SLM, the SDM is introduced. The Spatial Durbin model contains both spatial error term and spatial lag term. Wald and LR tests are used to estimate and compare the three spatial econometric models.

Finally, SEM, SLM and SDM were respectively constructed for the panel data. Due to the spatial correlation, the basic assumption model is no longer applicable, so we use the quasi-maximum likelihood method (QMLE) for statistical test, and the test results are shown in Table 6.

Table 6. Estimation and test results of SDM, SLM, and SEM models by fixed type.

Variable	SDM	SLM	SEM
lnGDPP	−0.1828 *** (−3.37)	−0.2991 *** (−7.31)	−0.3503 *** (−7.86)
(lnGDPP) ²	0.0386 *** (4.66)	0.0427 *** (6.27)	0.0516 *** (7.13)
lnPDEN	0.2859 *** (3.29)	0.1321 * (1.69)	0.1501 * (1.81)
lnTECH	0.0264 *** (2.6)	0.0241 ** (2.38)	0.0312 *** (3.00)
lnOPEN	0.003 (0.28)	−0.0085 (−0.76)	−0.0054 (−0.47)
lnURB	0.1862 *** (3.06)	0.1996 *** (3.24)	0.2246 *** (3.62)
lnPOPI	0.014 (0.69)	0.0334 (1.54)	0.0278 (1.31)
lnNUE	0.0439 ** (2.24)	0.0061 (0.35)	0.0328 * (1.74)
lnECU	0.3389 *** (6.53)	0.0286 (0.61)	0.1605 ** (2.19)
W*lnGDPP	0.0693 (0.94)		
W*(lnGEPP) ²	−0.0245 ** (−2.06)		
W*lnPDEN	−0.3979 ** (−2.34)		
W*lnTECH	−0.0136 (−0.78)		
W*lnOPEN	−0.0588 *** (−3.34)		
W*lnURB	−0.1748 * (−1.53)		
W*lnPOPI	−0.0382 (−1.00)		
W*lnNUE	−0.1331 *** (−3.91)		
W*lnECU	−0.7414 *** (−10.73)		
ρ	0.1216 ** (2.13)	0.1810 *** (3.10)	
λ			0.3259 *** (4.01)
R^2	0.4878	0.3101	0.2812
Log-likelihood	826.4837	745.0231	747.4552
sigma ²	0.0032 (16.86)	0.0043 *** (16.83)	0.0042 *** (16.50)
Wald_spatial_lag		62.99 ***	
LR_spatial_lag		162.92 ***	
(Assumption: SLM nested in SDM)			
Wald_spatial_error			61.53 ***
LR_spatial_error			158.06 ***
(Assumption: SEM nested in SDM)			

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors z in parenthesis.

As can be seen from Table 6, SLM passes the 1% significance test of Wald spatial lag test and LR spatial lag test, it rejects the null hypothesis $H_0: \theta = 0$, thus rejects the null hypothesis that “the model will degenerate into SLM”. SEM passes the 1% significance level test of Wald spatial error test and LR spatial error test, the null hypothesis $H_0: \theta + \rho\beta = 0$ is rejected, thereby rejecting the null hypothesis that “the model will degenerate into a spatial

error model". In conclusion, SDM is more suitable to describe the panel data of FNFP at provincial level in China.

3.3. Empirical Results of Fixed Effect Spatial Durbin Model

3.3.1. Results of EKC Validation and Influencing Factors Analysis

From the estimated results of the fixed effects model (Table 5) and the SDM model with fixed effects (Table 6), the linear term of GDPP is significantly negative, and the quadratic term of GDPP is significantly positive, which means that the relationship between FNFP and economic development is not the inverted U-shaped assumed by the classical EKC, but a U-shaped relationship.

From the estimation results of the SDM model with fixed effects (Table 6), it can be seen that PDEN, technology, urbanization and ECU have a positive impact on the growth of FNFP at a significant level of 1%. In the case of other factors unchanged, each 1% increase of these four factors can promote the FNFP increase by 0.2859%, 0.0264%, 0.1862% and 0.3389%, respectively. As urban income increases, the ECU will decrease, leading to a decline in the FNF. NUE has a significant positive effect on the increase of FNFP at a 5% level, with an elasticity coefficient of 0.0439. Strengthening the NUE and reducing the amount of nitrogen fertilizer application per unit of grain yield will slow down the FNF. The elastic coefficients of foreign trade and industrial structure are small, and has not passed the significance test.

According to the spatial lag coefficient, the elasticity coefficient of ρ at 5% significant level is 0.1216, which indicates that the panel data of FNFP in China have a positive spatial dependence, and the provincial FNFP is spatially clustered. The coefficients of $W*\ln OPEN$, $W*\ln NUE$, and $W*\ln ECU$ in the spatial lag terms of explanatory variables passed the 1% significance level test, and the values were -0.0588 , -0.1331 , and -0.7414 , respectively. This suggested that the explanatory variables in the SDM model with fixed effects also had spatial correlation, which means that foreign trade, NUE and ECU in neighboring provinces every increase an average of 1%, then the FNFP in this province changed considerably by -0.0588% , -0.1331% and -0.7414% in the circumstances of other variables keeps invariant. Moreover, $W*\ln PDEN$ reached the 5% significance level, its elasticity coefficient was -0.3979 . $W*\ln URB$ passed the 10% significance level test with a coefficient of -0.1748 .

3.3.2. Results of Spatial Effect Analysis

In fact, when estimating the spatial panel model, there are not many explanations for the coefficients of explanatory variables, that is, the coefficients of explanatory variables are not of great significance. What really needs to be explained are the direct and indirect effects, namely spatial spillover effects. Spatial spillover effect refers to the change of explanatory variables in adjacent regions caused by the change of explanatory variables in one region. The direct effect refers to the influence of the change of a certain factor in a certain area on the local area, and the indirect effect refers to the influence of the change of a certain factor in a certain area on its adjacent area. This indirect effect is transmitted through spatial interaction, and gradually decreases with the increase of the distance between spatial units [106].

In order to further analyze the effects of spatial interaction, this paper decomposed the influence of driving factors on FNF into direct effect and indirect effect according to the method provided by Lesage and Pace (2009) [84]. The effect of the explanatory variable on the FNFP of a local area is a direct effect. The impact of the explanatory variable on the FNFP in other regions is an indirect effect (i.e., the spatial spillover effect of influencing factors). The sum of the two is the total effect. Table 7 shows the effect decomposition results of SDM estimation based on fixed effects. The first and second columns of Table 7 show the direct and indirect effects of each explanatory variable on FNFP. The third column is the total effect of each explanatory variable on FNFP. The results show that:

Table 7. Decomposition of spatial effects.

Variable	Direct Effect	Indirect Effect	Total Effect
lnGDPP	−0.1796 *** (−3.29)	0.0496 (0.63)	−0.1300 * (−1.88)
(lnGDPP) ²	0.0376 *** (4.52)	−0.0211 * (−1.64)	0.0166 (1.39)
lnPDEN	0.2865 *** (3.49)	−0.3911 ** (−2.16)	−0.1046 (−0.61)
lnTECH	0.0263 *** (2.62)	−0.0120 (−0.67)	0.0143 (0.77)
lnOPEN	0.0015 (0.14)	−0.0622 *** (−3.32)	−0.0607 *** (−2.99)
lnURB	0.1860 *** (3.12)	−0.1648 (−1.43)	0.0212 (0.17)
lnPOPI	0.0134 (0.62)	−0.0393 (−1.00)	−0.0259 (−0.55)
lnNUE	0.0397 ** (2.16)	−0.1327 *** (−3.56)	−0.093 ** (−2.38)
lnECU	0.3265 *** (6.70)	−0.7581 *** (−10.6)	−0.4316 *** (−6.92)

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors *z* in parenthesis.

(1) The total and direct effects of GDPP on FNFP were negative. At the same time, the indirect effect of GDPP had a negative impact. The significance test of direct effect reached the level of 1%, the significance test of total effect passed the level of 10%, and the indirect effect did not reach the level of significance test. It shows that under the condition of other variables unchanged, GDPP can directly reduce the FNFP of local provinces.

(2) The total and indirect effects of PDEN on FNFP were negative, while the direct effects were positive. The direct effect and indirect effect reached the significance level of 1% and 5%, respectively, and the total effect did not pass the significance test. This means that the increase of PDEN may worsen the local nitrogen emissions, but has a mitigating effect on the FNFP of the surrounding provinces.

(3) The direct effect of technology development on FNFP is positive, with a significance level of 1%, while the indirect effect and the total effect do not pass the significance level test. This suggests that technology development has not reduced nitrogen emissions in the region.

(4) Foreign trade has a negative effect on the FNFP, the significant level is 1%, which illustrates that foreign trade can reduce the FNFP. The direct effect is positive without the significance level, the indirect effect is negative without the significance level of 1%. This implies that foreign trade is conducive to improving the FNFP in neighboring provinces.

(5) The direct effect of urbanization on FNFP is positive, and the significance level was 1%. while the indirect effect and total effect did not pass the significance level test. This makes clear that the development of urbanization stimulates nitrogen emissions in the region.

(6) The NUE has a negative effect on the FNFP, with a significant level of 5%, indicating that the FNFP could be reduced with the increase of NUE. The direct effect was positive, and the indirect effect was negative. The direct effect and indirect effect reached the significant level of 5% and 1%, respectively. This indicates that the increase of NUE may worsen the local nitrogen emission, but the increase in the FNFP of the surrounding provinces is not obvious.

(7) The total effect of the ECU on the FNFP is negative, with a significance level of 1%, which indicates that ECU can reduce FNFP. The direct effect was positive, and the indirect effect was negative. The direct effect and indirect effect reached the significant level of 5% and 1%, respectively. This explains that the reduction of ECU may improve the local nitrogen emission, but can increase the FNFP of surrounding provinces.

(8) The total effect, direct effect, and indirect effect of industrial structure on the FNFP did not pass the significance level test.

4. Discussion

The empirical results of this study provide strong evidence for the spatial correlation of food-related nitrogen emissions and the spatial spillover effect of FNF in China. The highly significant global Moran's *I* index and local Moran's *I* index proposed HH and LL spatial aggregation patterns of FNF. On the basis of the extended STIRPAT theoretical

framework and spatial econometric analysis approach, this study empirically verified that economic development, PDEN, technology, urbanization process, ECU and NUE are the driving forces of FNF in China.

Considering that the GDP–FNF model with quadratic term of GDPP has the best fitting, the valuable findings of this study are that there is a U-shaped EKC in the relationship between GDP and FNF, which is consistent with the research conclusion of Och (2017) [48], but our conclusion is inconsistent with the previous similar research results on NO_x emissions. Brajer et al. (2011) [52] and Luo et al. (2014) [51] believe that there is an inverted U-shaped EKC in the relationship between China's NO_x emissions and GDPP, while Ge et al. (2018) [70] verify that there is an inverted N-shaped EKC in this relationship. We found this inconsistency caused by two main reasons: (1) we applied the extended STIRPAT theory to the explained variable as the FNF, which is a composite index rather than a single substance pollutant environmental index, and the explanatory variable is relevant factors that has a significant contribution to the FNF, while Brajer et al. (2011) [52], Luo et al. (2014) [51] and Ge et al. (2018) [70] used a single substance pollutant environmental index of NO_x; (2) we first proposed the application of spatial panel data method to explore the relationship between FNF and economic development at a provincial level in China, The research objects of Brajer et al. (2011) [52] and Ge et al. (2018) [70] are Chinese cities, and the rural nitrogen emissions are not taken into account in the environmental pollution index, while the agricultural nitrogen emissions are indeed the main cause of NO_x emissions. Their research does not control the potential spatial autocorrelation between regional emissions, even if their samples are from cities that are usually spatially related. The existence of spatial relationship provides a potential explanation for the instability of EKC parameters, and the behavior of neighboring provinces will affect the behavior of the region itself.

In the study of influencing factors for NO_x emission, the main research methods currently are OLS regression model, unit root, cointegration test, and Granger causality test. With the in-depth research of econometric methods, vector error correction model (VECM), generalized Moment estimation (GMM), fully modified least squares method (FMOLS), generalized least squares estimator (GLS) and cross-section dependence test (Cross-section dependence test), co-integration autoregressive distribution lag (ARDL) boundary test, and other methods are generally widely used in the study of NO_x emission. The environmental indicator of this study is FNF, which is a composite environmental indicator to quantify the reactive nitrogen released during the food life cycle and its impact on the environment. The above-mentioned methods are applied to study the influencing factors of FNF in China's provinces, only discuss the development and change of FNF in the provinces themselves, while ignoring the spatial correlation and spatial characteristics of FNF between each province. Ge et al. (2018) [70] found that there was a significant inverted N-shaped EKC between NO_x emission and urbanization by using spatial econometric model. Using exploratory spatial data analysis and fixed effect SDM, this paper further concludes that China's inter-provincial FNF presents spatial agglomeration effect, and has a significant positive spatial dependence on the FNF of neighboring provinces. Therefore, this paper not only analyzes the influencing factors of provincial FNF development, but also fully explores the spatial spillover effect of provincial FNF development elements on surrounding provinces through spatial econometric method.

According to the analysis of the influencing factors of FNF, the ECU has the greatest impact on FNF. In the context of the acceleration of urbanization in China and the improvement of people's living standards, the decrease of ECU will improve the status of FNF, cause changes in nutritional diet, increase the proportion of plant-based foods, and reduce the ratio of animal-based foods. Another major factor is population growth leading to an increase in the FNF. Population puts great pressure on food security, resulting in nitrogen emissions at both ends of food production and consumption. Technology development has not dropped the FNF, which indicates that technology has not decreased nitrogen

emissions in food production, transportation and storage, in particular, the fertilization process of food production has not yet reflected green production.

The basic findings of this study refute the existence of EKC hypothesis of China's FNFP, thus emphasizing that the relationship between China's FNF and economic development is still in the early stage of EKC hypothesis. Among many influencing factors, ECU and use efficiency have been found to reduce the FNFP. Government decision-makers need to consider three policy-level measures: (1) At the food production side, the Chinese government has put forward the *Action Plan for Zero Growth in the Use of Fertilizers by 2020* [107], and implemented such technical paths as optimizing the structure of chemical fertilizer use, reducing the use of nitrogen fertilizer, applying organic fertilizer, improving fertilization methods, promoting precision fertilization, and steadily improving NUE. (2) At the food consumption side, policy makers advocate the social fashion of *Practicing Strict Economy, and Opposing Waste*, and repeatedly emphasize the need to stop food and beverage waste. At the same time, the *Opinions on Promoting Food and Beverage Economy and Opposing Food and Beverage Waste by Standardization* [108] issued by the government proposes to vigorously carry out the promotion activities of food and beverage saving standards. (3) At the regional level, the change of regional FNF and the spatial spillover effect of socio-economic factors on the FNF of neighboring provinces should be fully considered. When formulating relevant policies for the prevention and control of nitrogen pollution, Government functional sector should take into account the whole cooperation between provinces and regions. With the implementation of the policy and the development of economy, the turning point of FNFP will come in advance.

Due to the lack of relevant statistical data and parameters, it is more difficult to estimate the FNF and the error of the results, which contributes to the uncertainties of our study. Strengthening the research of food VNF based on the local situation in China is conducive to improving the accuracy of FNF estimation and reducing the nitrogen waste in each process from the perspective of food life cycle.

The influence of FNF on the environment of non-point pollution may be one of the directions of future nitrogen footprint research. In this paper, FNF and application of nitrogen fertilizer are analyzed. However, the nitrogen loss and waste in both ends of food production and consumption need further study. The main sources of non-point pollution caused by these nitrogen losses are analyzed. Then, the ecological effect of nitrogen footprint on the watershed environment is better evaluated.

5. Conclusions and Recommendations

5.1. Conclusions

In this study, the modified N-Calculator method proposed by Leach et al. (2012) [87] was used to calculate the FNFP of 30 provinces in China from 2000 to 2018. The extended STIRPAT theory was used as the research framework, the EKC idea was incorporated, and the exploratory spatial data analysis method was applied to study the spatial autocorrelation of China's FNFP. On this basis, the spatial Durbin panel model with fixed effect was adopted to study the influence and spatial effect of socio-economic factors on provincial FNF in China, and the following conclusions were drawn:

First, this study first verified the quantitative relationship between China's economy and FNFP. Compared with traditional econometric methods, spatial econometric techniques have never been used to explore the relationship between FNF and economy. Due to the spatial correlation of FNF to adjacent areas, the parameters estimated by the spatial panel data model are more reliable than those of the traditional panel model. The results show that the relationship between economy and FNFP is different from the current inverted U-shaped EKC hypothesis between economy and NO_x, but appears as a U-shaped EKC hypothesis curve, which clarifies that the relationship between China's FNF and economy is in the early stage of EKC hypothesis curve.

Second, in the study on the influencing factors of the FNFP, it is verified that the main driving forces of China's FNFP are the ECU, PDEN, urbanization, NUE, and technology.

The improvement of ECU and nitrogen utilization efficiency will slow down the FNFP in China. Population and urbanization have increased the FNFP in China, and technology does not slow down the FNF in China. It is proved that there is a positive spatial dependence of the FNFP, indicating that there is a significant spatial spillover effect in the FNFP. By means of spatial partial differential decomposition of the estimated results, ECU and nitrogen utilization efficiency can reduce the FNFP in the region, and can slow down the FNFP in the surrounding provinces.

Third, the paper provides a framework for the selection of spatial econometric model of FNF, LM test results of panel data show that the no fixed and spatial fixed panel model are the choice of this study. Further spatial LR and Wald spatial lag (error) test results show that SDM cannot be simplified as SAR or SEM form, SDM is more suitable for this research, the research on the spatial correlation problem of SDM can more fully explain the space effect, make up space lag panel overlook the defects of explanatory variables space effect, therefore, research on spatial correlation problem, can give priority to the SDM model. In the study of spatial correlation, SDM can more comprehensively explain the spatial effect and make up for the defect that the spatial lag panel ignores the spatial effect of explanatory variables. Therefore, SDM model can be given priority in the study of spatial correlation.

5.2. Policy Recommendations

First, the ECU, the PDEN, the Urbanization, the NUE, and the Technology are the main factors for the growth of FNFP in the province. By guiding healthy and scientific eating habits, reducing the proportion of meat and fish food in the diet structure, stopping food waste, and promoting the pattern of polite, saving, green, and low-carbon consumption, it is an effective way to guide the rapid growth of FNFP in each province. Furthermore, reducing nitrogen fertilizer application level per unit grain yield, and improving NUE, which are also effective suggestions to reduce the growth of FNFP in China's provinces. It is suggested to implement a strict nitrogen reduction policy, accelerate the development and promotion of new fertilizers such as slow-release fertilizer, water-soluble fertilizer, and biological fertilizer, and promote the replacement of inorganic nitrogen fertilizer by organic fertilizer in proportion. Second, the significant spatial spillover effect of FNFP suggests that policy makers, especially local governments, should not only pay attention to the local nitrogen emission, but also consider the impact of nitrogen emissions on neighboring provinces. The Chinese government should formulate policies at the national level to break the administrative boundaries of local governments and encourage local governments to actively participate in promoting food nitrogen emission reduction and economic growth. In addition, policy makers should formulate food nitrogen emission reduction plans at both the food production and consumption sides, advocate green production and green consumption, and strengthen the application and promotion of technology in nitrogen reduction.

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