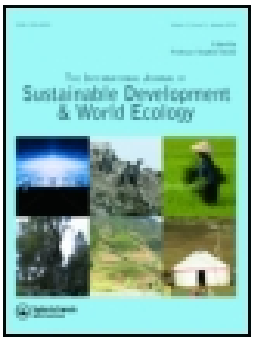

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Urban-rural nitrogen emission from household food consumption in China: spatial pattern and dynamics analysis

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ABSTRACT

The nitrogen emission from household food consumption (*NEHFC*) has played a vital role in sustainability development. Recent changes in household dietary have significantly accelerated reactive nitrogen emissions in China. However, the spatial patterns and dynamics of these flows between urban and rural areas remain unclear. Based on material flow and spatial-temporal analysis, our study investigated the patterns of Chinese urban-rural *NEHFC* during 1993–2015. Increasingly apparent regional disparities were found in both the spatial patterns of urban-rural *NEHFC* during the study period. Notably, the spatial autocorrelation of urban *NEHFC* demonstrated a 'U' type, compared with a recent decreasing *Moran's I* index of rural *NEHFC*. Moreover, the regional spatial-temporal variation of per capita urban *NEHFC* exhibited 'South (High)-North (Low)-Middle (Fast)' trend. By contrast, the hotspot of per capita rural *NEHFC* mainly concentrated in South-eastern China with a distinct regional changing of 'Middle-east (Fast) & west (Slow).' The Social-Economic and Regional-Development Index were far more critical than the Natural-Geographic Index to the spatial-temporal variation of per capita urban *NEHFC*, whereas the rural *NEHFC* was driven by the combined actions of all the three indexes. Our study highlighted the necessity of 'Location-Suitable' and 'Urban-rural recycling' nitrogen management strategies for reducing the risk of *NEHFC* in China.

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Spatial-temporal variation; urban-rural and national-regional disparity; sustainability development; nitrogen management; China

Introduction

Nitrogen *(N)* is an essential and irreplaceable element sustaining food production and global population after converting into reactive nitrogen *(Nr)* species (Galloway et al. 2003). However, its imbalances and overuses have caused a large amount of *Nr* to be released to the environment, adversely impacting on natural resources and environmental quality at local, regional and global scales (Cui et al. 2016). The phenomenon is primarily attributed to human activities which are associated with the demand for food (Smil 2004; Liu et al. 2010; Gu et al. 2015). As the food demand increases, the amount of *Nr* from anthropogenic production has been growing sharply over the past century, particularly from 15Tg *N* in 1860 to 156Tg *N* in 1995 (Liu et al. 2010). This growth may continue in the coming decades due to the rapidly increasing population and prosperity (Cui et al. 2013; Tilman and Clark 2014). And it will result in further excessive *Nr* accumulation and disproportional distribution in numerous nature-human reservoirs (Galloway et al. 2008; Canfield et al. 2010; Ma et al. 2010; Lin et al. 2014). In the past decade, the global *N* cycle has been reported to greatly suffer from disturbance by human activities (Vitousek et al. 1997; Galloway et al. 2008; Canfield et al. 2010; Liu et al. 2010). Therefore, significant achievements have been made in alleviating pollution through production-side end-of-pipe control technology and industrial cleaner production systems. However, evidence shows that they have been offsetting by another side effect of economic activity – unsustainable consumption patterns (Noorman 1998).

Human consumption activities are critical regulators of *Nr* flows and the associated spatial interactions, as the ecosystem is mainly subject to the direct impacts from anthropogenic perturbations (Liu et al. 2009; Erisman et al. 2013; Galloway et al. 2013; Bodirsky et al. 2014). The human household food consumption is amongst the primary driving forces of such impacts (Notarnicola et al. 2017; Luo et al. 2018). Recently, the human dietary is at the stage of transition to higher animal-derived food consumption, which leads to more nitrogen environmental emission than the plant-based food consumption, especially in emerging economies (Tilman et al. 2001; Reisch et al. 2013), and the ratio of the animal-derived food nitrogen to total food *Nr* is higher in urban diets than that in rural ones (FAO 2013; Tilman and Clark 2014). Such dietary changings are expected to continue, for over 2 billion people are moving into cities in the wave of global urbanization, especially in China,

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India, Southeast Asia and Africa (Habitat 2010). Furthermore, the transitions of dietary are more likely to cause more severe health and environmental problems (Tilman and Clark 2014). In 2015, United Nations proposed the Sustainable Development Goals (SDGs), directly mentioning four main goals in terms of food: ending hunger, achieving food security, improving food nutrition and promoting sustainable production-consumption environment (UN 2015; Development Initiatives 2017; Leal Filho et al. 2018). The increasing nitrogen emission from household food consumption *(NEHFC)*, which has been exerting huge impacts on sustainable development of the society, economy, and environment, has attracted a wide range of attention (Neset et al. 2006; Zhao et al. 2008; Vermeulen et al. 2012; Green et al. 2015; Springmann et al. 2016).

China, as the largest *Nr* consumer and the most populous country in the world, has been undergoing the most significant urbanization during the last few decades (Yang 2013). It is a typical example demonstrating how urbanization, dietary changing, urban-rural disparity, and regional differences impact *NEHFC* in an emerging economy. China's socio-economic transformation has been accompanied by the transition of household dietary towards higher shares of animal-derived foods (Bai et al. 2014). Furthermore, most consumption of animal-derived food is in urban settings (Hou et al. 2013). With the blocked recycling of nitrogen from cities to rural areas, massive amounts of nitrogen accumulate in the urban environment after household consumption (Alberti et al. 2003; Lin et al. 2014; Xiao et al. 2017). What is more, regional heterogeneity exists in provincial dietary patterns. And the uneven regional development also results in different regional nitrogen management practices. Therefore, new complexities appear in the Chinese environment-nutrition nexus (He et al. 2018).

For effectively assessing and solving the Nr-driven problems, it is essential that having a comprehensive understanding of nitrogen emission and its spatial distribution pattern in China. Most of the literature focused on the nitrogen flows at the national scale (Ti et al. 2012; Gu et al. 2015; Shi et al. 2015; Cui et al. 2016) and regional scale (Kimura and Hatano 2007; Han et al. 2011; Ma et al. 2014). Limited works compared urban-rural *Nr* emission from household food systems during the period of China's rapid urbanization. The historical variation of urban-rural *NEHFC* in China has been further explored (Hou et al. 2013; Gao et al. 2018). However, local features of spatial-temporal variation were still ignored. Here, a material flow analysis (MFA) of Chinese urban-rural *NEHFC* during 1993–2015 was presented, covering its creation, flux, and accumulation in different environmental systems (soil, atmosphere, and water body) (Figure 1). Combined with the spatial-temporal analysis, this study aimed (i) to analyze the variation pattern of urban-rural *NEHFC* at the national level. (ii) to compare the regional spatial-temporal variation patterns of per capita urban-rural *NEHFC* at the provincial level. (iii) to identify the critical drivers of household food-consumption-sourced *Nr* emission in both the urban and rural areas. Our study hopes to provide a reference for scientific control and alleviation of the adverse impact of excessive *NEHFC*, as well as regional *Nr* management in mainland China and other emerging countries.

Materials and methods

System definition

The complete metabolism process of *Nr* emission from household food consumption includes the metabolism in the social-ecosystem, covering the food consumption, human metabolism, waste treatment (Wang and Lin 2014), and the biogeochemical cycles in natural ecosystems. Our study, with the boundary of social ecosystems, mainly focused on the urban-rural flows of *NEHFC* at the provincial level respectively. Several future analyses were conducted in 31 provinces in mainland China, excluding Hongkong, Macao, Taiwan because of data unavailability.

Model and methods description

Model of urban-rural NEHFC

The material flow analysis (MFA) was applied for quantifying the flows of urban-rural *NEHFC* in mainland China. Based on the per capita food consumption in a year, food was divided into nine categories: grain, pea, vegetable, fruit, meat, oil, egg, dairy product, and seafood. The division between urban and rural diet was based on national statistical yearbooks (NBSC 1994–2016) and provincial statistical yearbooks (CNKI 2003). The formula of nitrogen contained in food is as follows.

$$W_p = \sum_{i=1}^{n} W_{pi} \tag{1}$$

$$W_{pi} = W_i \times P_i \tag{2}$$

Where W_P referred to the total amount of *Nr* included in per capita household food consumption. W_{pi} is the quantity of *Nr* in per capita food *i* consumption. W_i is the amount of per capita food *i* consumption. P_i is the nitrogen conversion coefficient of food *i*. Its value depends on the relationship between the protein and the *Nr* content of food *i*, which is equal to the protein content divided by 6.25 (Table 1). The nitrogen conversion coefficients of the above nine category foods were obtained from the protein content of foods referring to the 'Common Food Nutrition Table' (Feng and Shen 2005). n is the types of household food consumption, n = 9.

In our model, food is separated into eatable and non-eatable portions. The edible part covers those going

Table 1. The nitrogen conversion coefficients of household food (g/kg).

Items	Grain	Pea	Vegetable	Fruit	Meat	Oil	Egg	Dairy Product	Seafood
Nitrogen Content	18.17	58.08	1.76	1.60	29.22	31.10	20.48	5.28	28.77

through the human metabolic process from eating behavior. Most of the human metabolic products enter the waste treatment process along with human manure. The non-edible portion refers to the kitchen waste covering the inedible and discarded food. Only partial kitchen waste has been treated, with the rest releasing to the environment.

The urban ecosystem is a combination of high nutrient density fluxes and disrupted *N* cycling (Grimm et al. 2008; Lin et al. 2014; Ma et al. 2014). Blocked recycling leads to the enormous accumulation of nitrogen in urban environments after household food consumption (Alberti et al. 2003). For the treatment of kitchen waste, the landfill is the primary treatment process in urban areas, resulting in the deposition of the soil environment. The *Nr* gas by the landfill is minimal, which could be negligible in the calculation according to '2006 IPCC Guidelines for National Gas Inventories' (Eggleston et al. 2006). The treatment by incineration is seldom because of the large amount of water and organic matters contained in the garbage, and the emissions generally directly discharge into the atmosphere. For the treatment of urban human manure, the manure is collected into the sewage treatment system through the pipeline, and the sludge is mostly directly discharging into the soil environment. Moreover, both the remaining treated and untreated sewage are released into the water body. Nitrogen contained in N_2O, NH_3, and other gases discharges directly into the atmosphere through the nitrification and denitrification process, especially during the procedure of the composting of kitchen waste and the sewage treatment.In contrast, China has a long history of utilizing organic fertilizers and food waste for livestock farming, especially in rural areas (Luo et al. 2018). A large part of rural kitchen waste is used as livestock food. And the human manure in rural areas is mostly released into the soil environment as farming fertilizer after the process of composting. Detailed descriptions of the urban-rural MFA models could be seen in Figure 1 and Tables 2–4.

The discharge terminals of urban-rural *NEHFC* include atmosphere, soil and water bodies (Nr_{flux}), Based on mass balance, a equation of the total *NEHFC* emission ($NEHFC_{total}$) was obtained as follows:

$$NEHFC_{total} = \sum Nr_{flux} \tag{3}$$

The pattern analysis of spatial-temporal variation in urban and rural NEHFC

The overall pattern analysis – – coefficient of variation analysis (CV) and global Moran's I. *The coefficient of Variation Analysis (CV), eliminating the impacts of units and means on the results, has been widely used to explore the spatial disparity (Reed et al. 2002). In this paper, the C_V was used to measure the overall spatial disparity of per capita NEHFC between urban and rural areas, as expressed below*:

$$\mathrm{Cv_a} = \frac{S_a}{\overline{X_a}} \times 100\% = \frac{1}{\overline{X_a}} \left[\frac{\sum_{i=1}^{n} (X_{ai} - \overline{X_a})^2}{n-1} \right]^{\frac{1}{2}} \times 100\% \tag{4}$$

Where Cv_a is the coefficient of variation in the year *a*. S_a is the unbiased estimate of the standard deviation of per capita *NEHFC* . $\overline{\mathrm{X_a}}$ is the mean of the national per capita *NEHFC* in the year a. X_{ai} is the value of per capita *NEHFC* in each province (cities) *i*, *n* is the number of provinces in this study, n = 31.

The spatial autocorrelation analysis in the exploratory spatial analysis method (ESDA) includes global and local *Moran's I* index. The global *Moran's I* index (Anselin 1999) was applied into this paper to examine the national spatial autocorrelation of *NEHFC* in China, as shown below:

$$I_c = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{X})(x_j - \bar{X})}{\sum_{i=1}^{n}(x_i - \bar{X})^2} \tag{5}$$

Where *N* is the number of provinces indexed by *i* and *j*. x_i and x_j are the provincial per capita *NEHFC*. $\bar{X}$ is the mean value of x_i or x_j. w_{ij} is an element of spatial relationships. The spatial matrix – 'contiguity edges &corners' was also introduced in this study. The values of global *Moran's I* range from −1 to 1. The positive value shows a significant positive spatial autocorrelation and the inverse for the negative values. When the global *Moran's I* index approaches 0, it suggests that the spatial pattern has no spatial autocorrelation. The significance test is performed with the standardized statistic Z test. $|Z|>1.96$, indicates that the spatial autocorrelation is significant at the 95% confidence level.

The regional pattern analysis – the empirical orthogonal function (EOF analysis)

The empirical orthogonal function (*EOF analysis*) (Lorenz 1956) was adopted in this study to identify the local patterns of the spatial-temporal variation of urban and rural *NEHFC*. The 'local patterns' refers to the specific changing trend of different areas in mainland China. *EOF*, also known as eigenvector analysis, principal component analysis or nature orthogonal function, is usually used to analyze the temporal and spatial variation characteristics of a spatial-temporal panel (X_{ij}).

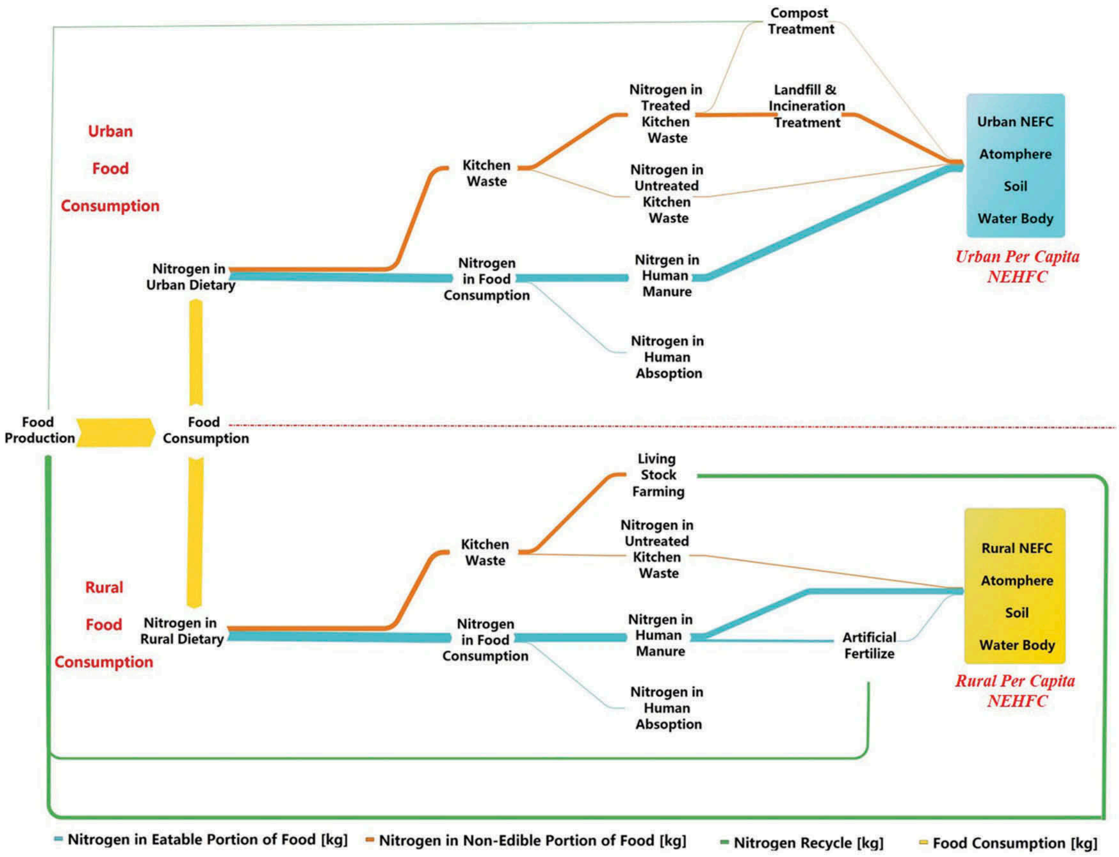

Figure 1. The material flow analysis of nitrogen environmental emission from household food consumption.

Table 2. Calculation parameters of the *NEHFC*.

Parameters	Unit	Values	Reference
Kitchen Waste Contained in Food Consumption	%	33.33	(Qu et al. 2009)
The Food Absorption Rate of Human Body	%	0.02	(Wei et al. 2008)
The Discharge Rate of Human Manure	%	0.88	(Liu et al. 2006)
Nitrogen Volatilized Rate from Manure	%	24.5	(Zhu 2008)
The Kitchen Waste Used for Rural Livestock Farming	%	80	(Ma et al. 2010)
N_2O Emission Factor	Kg N_2O/kg N	0.005	(Eggleston et al. 2006)
The Rate of Human Manure Used as Fertilizer	%	30	(Luo et al. 2018)
The Nitrogen Removal Rate of Human Manure	%	60	(Shi 2014)

$$X = (X_{ij}) = \sum_{k=1}^{m} \lambda_i V_{ik} T_{kj} \quad (6)$$

$$\lambda_i - \lambda_{i+1} \geq \lambda_i \sqrt{\frac{2}{n}} \quad (7)$$

After orthogonal decomposition, the space-time sample is divided into the characteristic vector fields (V_{ik}) and their corresponding temporal coefficients (T_{kj}). The characteristic vector field represents the spatial pattern of the spatial-temporal variation. All the characteristic vectors are mutually orthogonal. The maximum absolute value of the characteristic vector presents most sensitive regions with the abnormal increasing or decreasing. The annual weight of the characteristic vector (corresponding temporal coefficients) reveals the yearly contribution to the spatial patterns. Every model is constituted by their characteristic vector field and corresponding temporal coefficients, sorted by their contribution rates. The model with the maximum contribution rate is considered as the leading model (labeled as the first Model), reflecting the general pattern of the spatial-temporal variation. The rest models formulated by other characteristic vector fields and corresponding temporal coefficients indicate different particular variations. The typical models are selected by significance tests according to the error range of the Eigen root (λi) proposed by North (North et al. 1982). If eigenvalues of the adjacent models fail to satisfy the equation (7), then the following models are not the typical ones.

Driving force analysis of spatial-temporal variation in urban and rural NEHFC

According to the core idea of the Geographical detector (Wang et al. 2010), the study target always exists in specific spatial locations, and the relative environmental factors have different spatial patterns. The geographical detector is generally used to search for stratified spatial

Table 3. Calculation formulas of per capita urban *NEHFC*.

Items	Formulas
Nitrogen Contained in Kitchen Waste	Kitchen waste contained in household food consumption * $W_{P\ .Urban}$
Nitrogen Contained in Human Food Absorption	($W_{P.Urban}$ − Nitrogen contained in kitchen waste) × The food absorption rate of the human body
Nitrogen of Human Manure	($W_{P.Urban}$ − Nitrogen contained in kitchen waste) × The discharge rate of human manure
Nitrogen Contained in Treated Kitchen Waste	The nitrogen contained in kitchen waste × Harmless treatment rate of urban kitchen waste
Nitrogen Contained in Untreated Kitchen Waste	The nitrogen contained in kitchen waste - Nitrogen contained in treated kitchen waste
Nitrogen Contained in Treated Human Manure	Nitrogen of human manure × Sewage treatment rate
Nitrogen Contained in Untreated Human Manure	Nitrogen of human manure − Nitrogen of urban sludge − Nitrogen of treated urban wastewater - Nitrogen emissions from sewage treatment
Nitrogen of Urban Sludge	The nitrogen contained in treated human manure × The nitrogen removal rate of human manure
Nitrogen of Treated Urban Waste Water	The nitrogen contained in treated human manure × (1-The Nitrogen removal rate of human manure)
Nitrogen Contained in Urban Food Waste Compost Treatment	The nitrogen contained in treated kitchen waste × Percentage of composting of waste treatment
Nitrogen Contained in Urban Food Waste Incineration Treatment	The nitrogen contained in treated kitchen waste × Percentage of incineration of waste treatment
Nitrogen Contained in Urban Food Waste Landfill Treatment	The nitrogen contained in treated kitchen waste × Percentage of landfilling of waste treatment
Nitrogen Volatilized from Manure	The nitrogen contained in urban food waste compost treatment ×Nitrogen volatilized rate from manure
Nitrogen Emissions from Sewage Treatment	The nitrogen contained in treated human manure×$N_2$0 emission factor
Nitrogen Loading of Atmosphere (Nr_{flux})	The nitrogen contained in urban food waste incineration treatment + Nitrogen emissions from sewage treatment + Nitrogen volatilized from manure
Nitrogen Loading of Soil (Nr_{flux})	The nitrogen contained in untreated kitchen waste + Nitrogen of urban sludge + Nitrogen contained in urban food waste landfill treatment
Nitrogen Loading of Water (Nr_{flux})	The nitrogen contained in untreated human manure + Nitrogen of treated urban wastewater

Table 4. Calculation formulas of per capita rural *NEHFC*.

Items	Formulas
Nitrogen Contained in Rural Kitchen Waste	Kitchen waste in household Food Consumption * $W_{P.}$ *Rural*
Nitrogen Contained in Human Food Absorption	($W_{P.Rural}$ − Nitrogen contained in kitchen waste) × The food absorption rate of the human body
Nitrogen of Human Manure	($W_{P.Rural}$ − Nitrogen contained in kitchen waste) × The discharge rate of human manure
Nitrogen Contained in Kitchen Waste Used for Rural Livestock Farming	The nitrogen contained in rural kitchen waste × The proportion of kitchen waste used for rural livestock farming
Nitrogen Contained in Untreated Rural Kitchen Waste	The nitrogen contained in rural kitchen waste − Nitrogen contained in kitchen waste used for rural livestock farming
Nitrogen Content in Treated Rural Human Manure	Nitrogen of human manure × The rate of human manure used as fertilizer
Nitrogen Contained in Untreated Rural Human Manure	Nitrogen of human manure − Nitrogen contained in treated rural human manure
Nitrogen Volatilized from Treated Human Manure	The nitrogen contained in treated rural human manure × Nitrogen volatilized rate from manure
Nitrogen Loading of Atmosphere (Nr_{flux})	Nitrogen volatilized from treated human manure
Nitrogen Loading of Soil (Nr_{flux})	The nitrogen contained in untreated rural kitchen waste
Nitrogen Loading of Water (Nr_{flux})	The nitrogen contained in untreated rural human manure

heterogeneity of the target, and to examine its association with influential factors based on the consistency of their spatial distributions. The q value is measured as:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \delta_h^2}{N\delta^2} \quad (8)$$

Where N and δ^2 refer to the number of units and the variance of Y (provincial per capita *NEHFC*), respectively. Y is composed of L strata, N_h and δ_h^2 stand for the number of the units and the variance of Y in stratum h, respectively. The strata of Y are obtained from a partition of Y by an explanatory variable X, which is a categorical variable. The value of q ranges from 0 to 1. The higher value of q indicates the more critical role of X to the spatial pattern of Y.

To discuss the driving forces of the spatial-temporal variation of urban and rural *NEHFC* respectively, twelve potential drivers (sub-indexes) were extracted from the literature (De Irala-Estevez et al. 2000; Liu et al. 2003; Yu et al. 2012; Zhao et al. 2017), and collected from statistic yearbooks from 1994 to 2016 with the provincial view respectively. All of the sub-indexes were classified into three groups, separately labeled as Nature Geographical Index (G), Regional Development Index (D), Social-Economic Index (S) (Table 5). Moreover, the sub-indexes in Social-Economic Index (S) were obtained with the view of urban and rural area respectively.In our study, the provincial indexes of wet-dry zoning (G1), landform (G2), Altitude (G3) were assumed to experience no change during the study period. To diminish the interannual fluctuation of the outcome, the 3-year average of per capita *NEHFC* and numerical sub-indexes in each province were obtained for calculation. Furthermore, the rest numerical variables had also

Table 5. Driving forces of spatial-temporal variation of urban-rural *NEHFC*.

Main Category	Sub index	Data &Classified Description	Data Sources
Nature Geographical Index (G)	wet-dry zoning (G1)	Arid area, Semiarid Area, Arid/Semiarid Area, Humid/Semi-humid Area, Humid Area, Wet Area, and Over-Wet Area	(RESDC 2017)
	landform (G2)	Plain, Platform, Hill and Mountain Land.	(RESDC 2017)
	Altitude (G3)	Altitude: 0 ~ 600 m, 600–2600 m, Above 2600 m	(Jiang and Yang 2009; RESDC 2017)
Regional Development Index (D)	Regional Accessibility (D1)	The factor represents the development level of the local infrastructure(The provincial highway mileage/the area of the province)	(MOHURD 1994–2016)
	urbanization rate (D2)	The factor represents the development level of the local economy.	(MOHURD 1994–2016)
	Regional Foreign Trade Intensity (D3)	The factor represents the impact of external commercial activities in this region (The proportion of the total volume of import and export trade in the provincial GDP)	(MOHURD 1994–2016)
	Local Per Capita GDP (D4)	The factor represents the development level of the local economy.	(MOHURD 1994–2016)
Social-Economic Index (S)	Engel Coefficient (S1)	The factor represents the provincial purchasing power of residents	(CNKI 2003)
	Price Level (S2)	The factor represents the provincial purchasing power of residents	(CNKI 2003)
	Family Scale (S3)	The factor represents the influence of social factors on the purchasing choice of residents	(NBRSES 1994–2016; NBSCPES 1994–2016)
	Education Level (S4)	The factor represents the influence of social factors on the purchasing choice of residents	(NBRSES 1994–2016; NBSCPES 1994–2016)
	Per Capita Disposable Income (S5)	The factor represents the provincial purchasing power of residents	(NBRSES 1994–2016; NBSCPES 1994–2016)

(i) RESDC is short for 'Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences.'
(ii) Social-Economic Index (S) selected on the view of urban and rural respectively

experienced 5-level discretization by nature break. Finally, the 'two-step cluster' was taken to the sub-indexes under the same driving factor group, and the strata results of the three groups were introduced into the Geo-detector.

Dataset description

Data were derived from the following sources: *(i)* National and provincial statistical databases, including 'Provincial statistical Yearbooks 1994–2016 (*CNKI knowledge Network Service Platform*),' 'China Statistical Yearbook 1994–2016,' 'China Rural Statistical Yearbook 1994–2016,' 'China Urban Construction Yearbook 1994–2016,' 'The Population and Employment Statistic Yearbook 1994–2016'; *(ii)* Nature geographic data mainly obtained from the 'Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences *(RESDC)* (*http://www.resdc.cn*)'; *(iii)* A detailed description of parameter values are available in Table 2.

Result

The spatial-temporal variation of per capita NEHFC in urban and rural areas

The national spatial-temporal variation patterns of urban and rural NEHFC

Two distinct historical variations could be distinguished regarding interannually national average value of urban-rural per capita *NEHFC*. As shown in Figure 2, urban *NEHFC* kept stable before 2007 and then soared up, from 3.13 kg/per capita in 2007 to 3.77 kg/per capita in 2015. In contrast, the *NEHFC* in rural areas dropped down remarkably during the study period, from 3.07 kg/per capita(1993)to 2.42 kg/per capita(2015).

As shown in Figure 3, the national spatial disparities (CV) of the provincial per capita urban *NEHFC* presented a rising trend at three distinct phrases of 1993–2000 (Phase I, steady at around 12.60%), 2000–2009 (Phase II, dramatically increasing to 20.82%) and 2009–2015 (Phase III, stabilizing at approximately 20%). By contrast, the national CV of provincial per capita rural *NEHFC* firstly kept steady before 2008, then significantly increased in the following years, from around 11.56% (1993–2008) to 17.18% (2015). In summary, the regional disparities of provincial per capita urban-rural *NEHFC* have been both enlarging in the past 23 years.

All the annually Global Moran's *I* indexes of provincial per capita urban-rural *NEHFC* were above 0 (Figure 2), showing positive spatial autocorrelation of the national pattern in each year. However, they underwent entirely different changing trends. The *Moran's I* of provincial per capita *NEHFC* in urban area exhibited an evident 'U' type. Specifically, spatial autocorrelation of provincial per capita *NEHFC* firstly weakened before 2009, then enhanced with an increasingly obvious phenomenon of 'High-High, Low-Low Spatial Aggregation' in the urban area of Mainland China. By contrast, all the annually values of *Moran's I* for the provincial per capita rural *NEHFC* remained steady first and then rapidly decreased after 2008. The pattern of 'High-High, Low-Low Spatial Aggregation' has weakened in recent years.

The local patterns of spatial-temporal variation of urban and rural NEHFC

To explore local characteristics of spatial-temporal variation, the annual anomaly values of provincial per capita urban-rural *NEHFC* were introduced into the *EOF* analysis respectively. The significance test proposed by North (North et al. 1982) was carried out in our study.

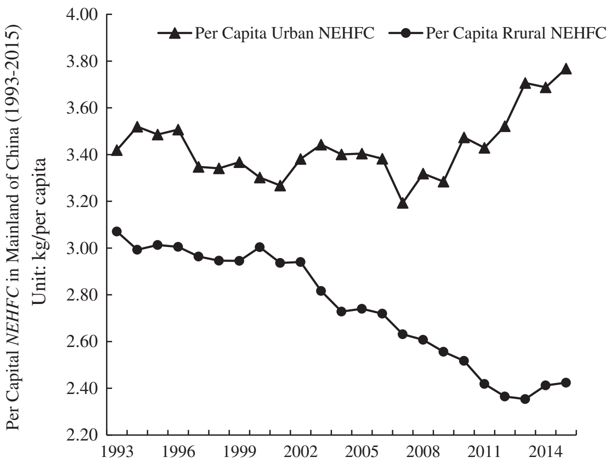

Figure 2. Historical variation of the national average per capita NEHFC in mainland China (1993–2015).

Therefore, Each top two models of *EOF* analysis on the urban *NEHFC* (contribution rate: 68.66% and 16.05%) and on the rural *NEHFC* (contribution rate: 63.7% and 17.25%) were separately applied into the present study (Table 6).

As shown in Figure 4, the first model was the leading model, with the maximum contribution rate of 68.66%. It revealed the basic pattern of local spatial-temporal variation displaying a visible 'north-south' disparity in mainland China, the provinces with higher per capita urban *NEHFC* mainly concentrated in the south of the 'Zhejiang-Tibet line.' The regions covering Beijing, Tianjin, Fujian, and Guangdong, were in the position of the maximum values. The variation tendency of the temporal coefficients could be separated into three phases (before 2000,2000–2009, after 2009). Combined the historical variation of per capita *NEHFC* in the urban area, the growth rate of per capita urban *NEHFC* in Southern China (the negative area) was higher than that of the rest areas along with the fluctuated negative growth of the corresponding temporal coefficients, and the regional disparities among the provinces were enlarging, especially during 2000–2009.

The second model had a contribution rate of 16.05%, demonstrating a particular pattern of the spatial-temporal variation of per capita urban *NEHFC*. The areas with negative values covering 19 provinces (cities) with a spatial distribution of 'T' type in mainland China. Along with the tendency of temporal coefficients, the provincial per capita emissions in the 'T' (Middle) areas experienced faster growth than the other regions. In addition, the urban *NEHFC* in the 'T' area exceeded other regions on *Nr* emission of the after 2009, showing significant high-high aggregation with the neighbor provinces.

As indicated in Figure 5, the first model had the maximum contribution rate of 63.70%which was divided into four parts and showed 'Belts' disparities in regional-temporal variation. 'Fujian – Tibet' ' Liaoning – Inner Mongolia' were the two 'negative belts'with the other two 'positive belts.' And the hotspot of provincial per capita rural *NEHFC* gathered in the 'Southeast' of China. Meanwhile, the temporal coefficients firstly kept stable before 2008, then fell significantly. Combined the

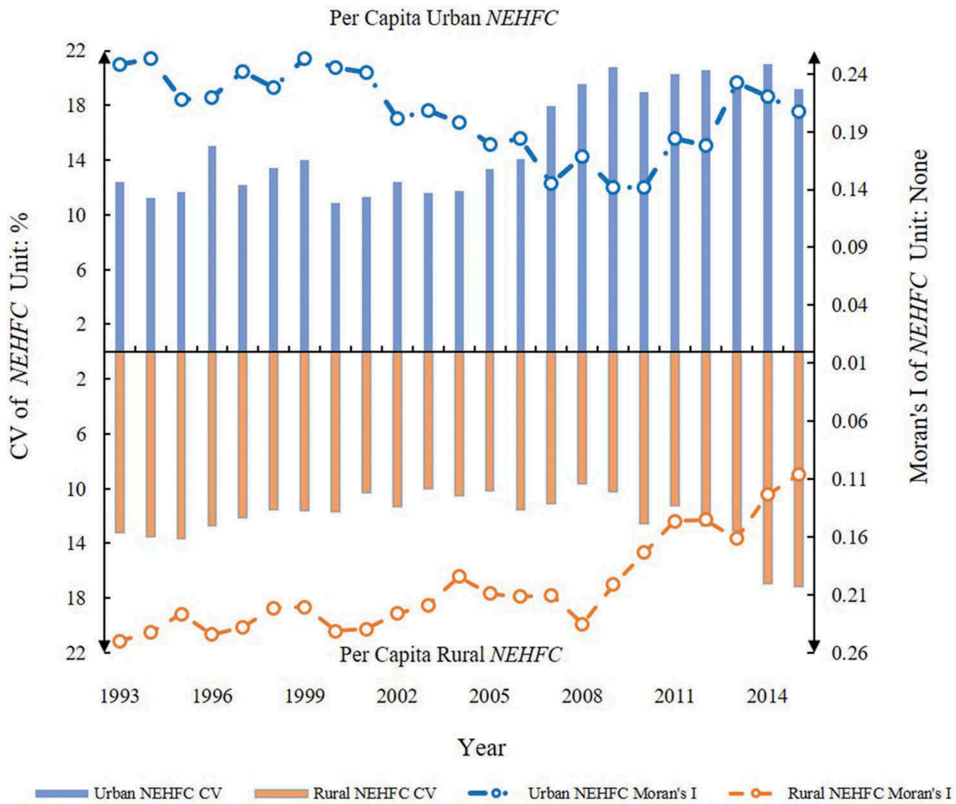

Figure 3. The national spatial-temporal variation of provincial per capita NEHFC in mainland China (CV and Moran's I).

Table 6. North significance test for EOF analysis (North et al. 1982).

Urban *NEHFC*			Rural *NEHFC*		
Eigen root (λ_i)	Contribution Rate	North Test	Eigen root (λ_i)	Contribution Rate	North Test
6.1584	68.66%	0.7662	2.1547	63.70%	0.7293
1.4396	16.05%	0.7622	0.5833	17.25%	0.6977
0.3424	3.82%	0.2667	0.1763	5.21%	0.1111
0.2511	2.80%	0.2852	0.1568	4.63%	0.5524
0.1795	2.00%	0.3564	0.0702	2.07%	0.2490
0.1155	1.29%	0.1789	0.0527	1.56%	0.0902
0.0949	1.06%	0.2119	0.0479	1.42%	0.3150
0.0748	0.83%	0.1068	0.0328	0.97%	0.2348
0.0668	0.74%	0.1332	0.0251	0.74%	0.2611

historical variation of per capita *NEHFC* in the rural area, the local spatial-temporal pattern of rural per capita *NEHFC* showed a feature of 'Belts' disparity, with the positive area decreasing faster than the negative regions. Moreover, the regional gap became increasingly apparent since 2008.

The second model had a contribution rate of 17.25%, revealing the particular local change of the per capita rural *NEHFC* in mainland China. During 1993–2015, the falling rate of the Middle-east region was apparently faster than the western part. Before 2000, the annual patterns of per capita rural *NEHFC* showed a feature of 'Middle-east (high) and West (low),' which, however, changed to the feature of 'West (high) and Middle-east (low)' in the following years. Notably, several regions, such as Beijing, Tianjin, Shanghai, presented different changing trend on per capita *NEHFC* compared with the rest provinces in Middle-east of mainland China, especially after 2000.

Driving forces of spatial-temporal variation in per capita urban and rural NEHFC

Compared with the *q* values of the three index groups, the Social-Economic Index (S) and Regional Development Index (D) were observed to be far more critical than those of the Natural Geographic factor (G) on per capital urban *NEHFC* (Figure 6). Specifically, the Regional Development Index (D) posed an apparent fluctuating influence on per capita urban *NEHFC*. The q values of Social-Economic Index (S) enhanced steadily since 1999–2001, by contrast with a noticeable falling in the tendency of Nature Geographic Index(G).

As shown in Figure 7, the q values of the three indexes presented no significant difference, indicating the combined effect on the per capita rural *NEHFC*. Before 2011–2013, the Regional Development Index (D) had stronger power than the Social- Economic Index (S). However, during 2011–2013, the Social-Economic Index (S) became the leading factor. The q value of the Natural

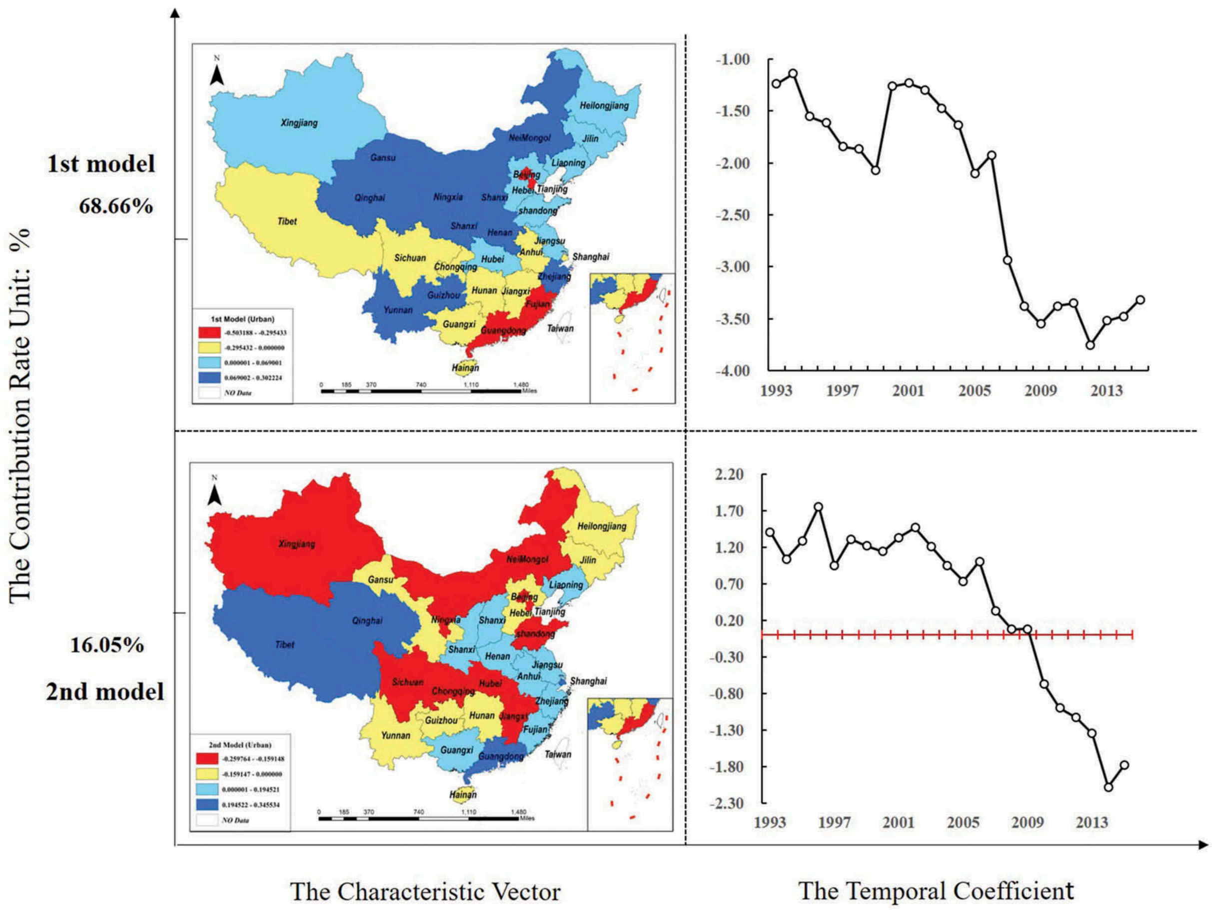

Figure 4. The local spatial-temporal variation of provincial per capita urban *NEHFC* (EOF analysis).

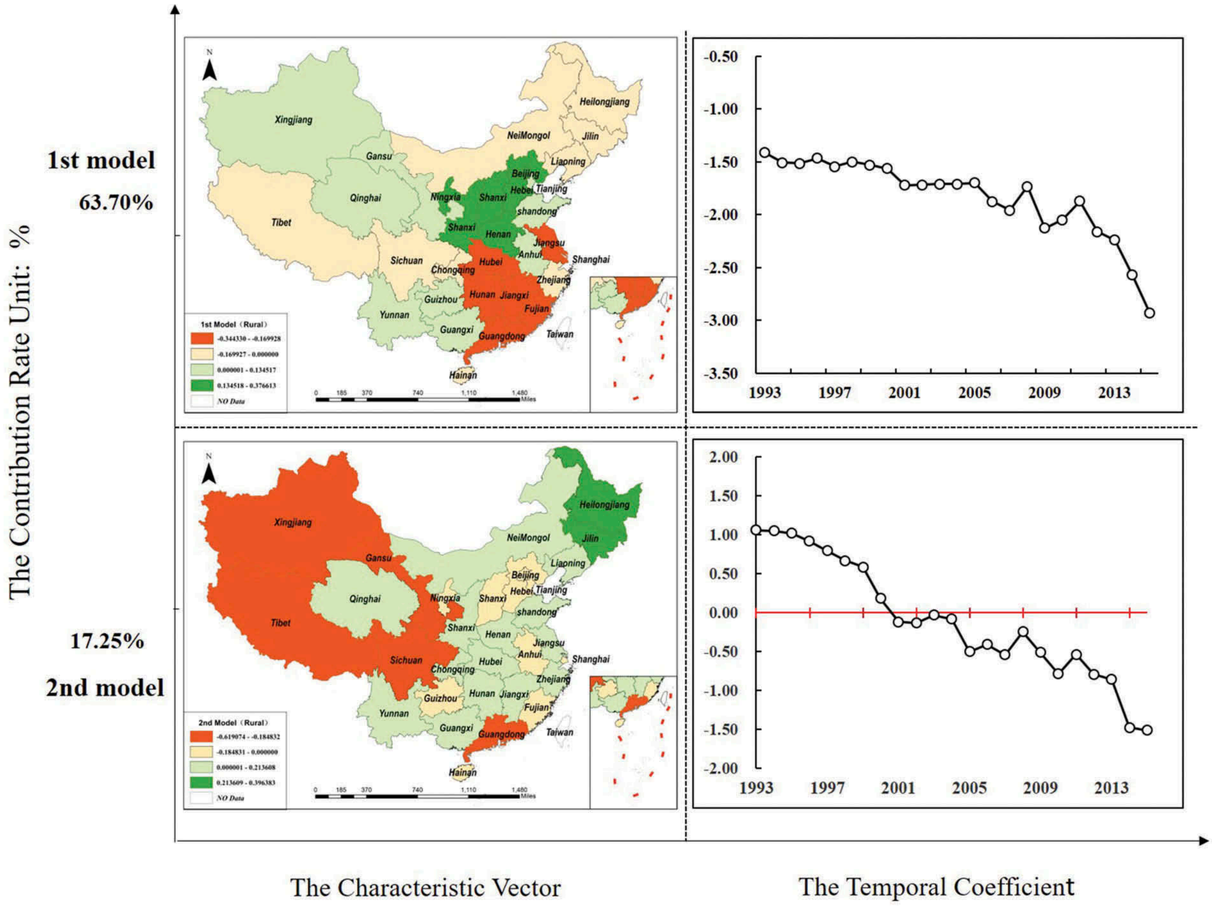

Figure 5. The local spatial-temporal variation of provincial per capita rural NEHFC (EOF analysis).

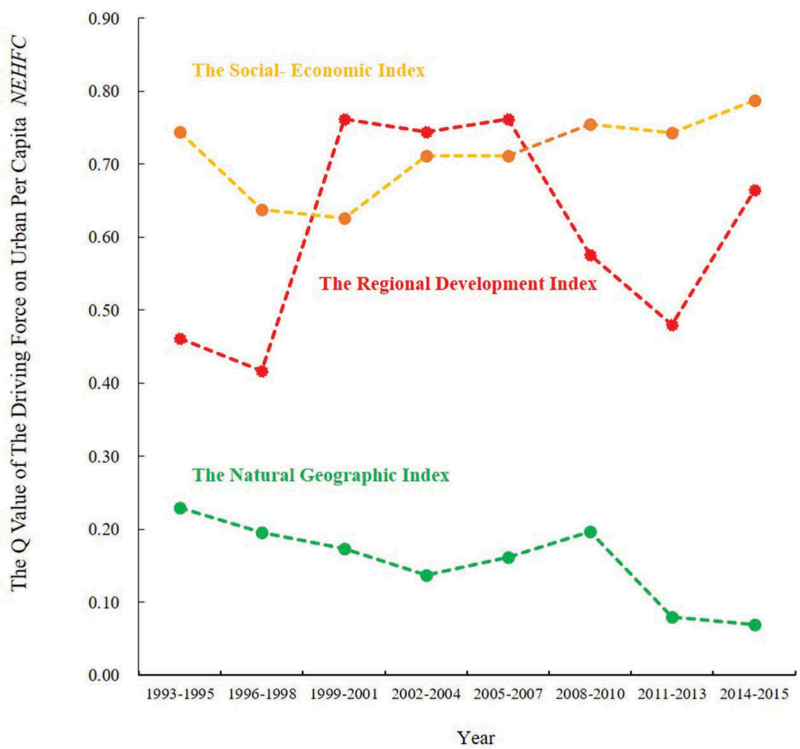

Figure 6. Driving force analysis of urban *NEHFC* spatial-temporal variation, q values is the index to test the association between the spatial-temporal variation of per capital *NEHFC* and impact factors (Social-economic index (S), Regional development index (D), The natural geographic factor (G)) based on the consistency of their spatial distributions.

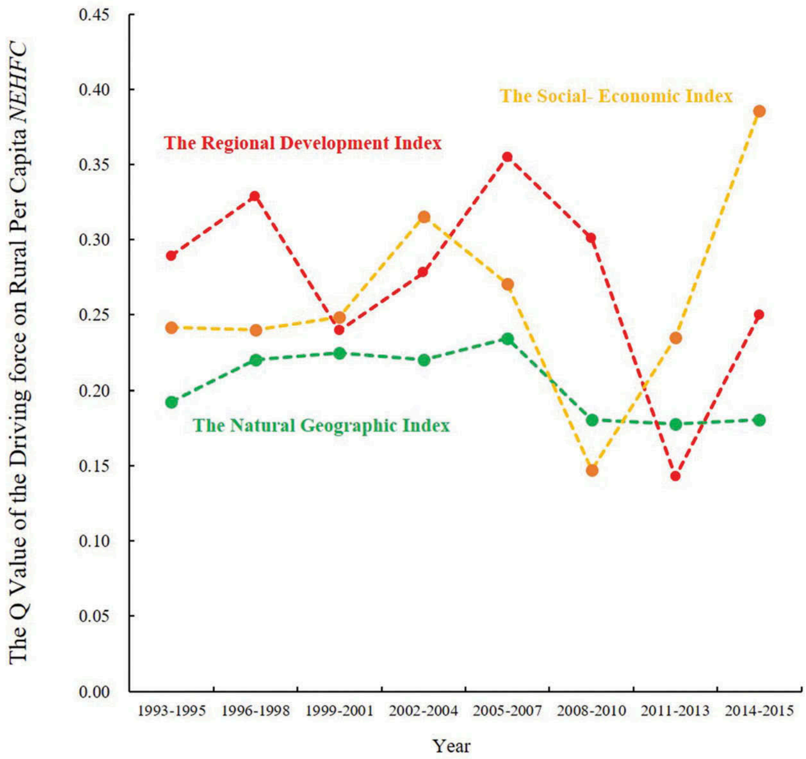

Figure 7. Driving force analysis of rural spatial-temporal variation, q values is the index to test the association between the spatial-temporal variation of per capital *NEHFC* and impact factors (The social-economic index (S), The regional development index (D), The natural geographic factor (G)) based on the consistency of their spatial distributions.

Geographic Index (G) showed a downward trend from 0.22 before 2005 to about 0.18 in recent years.

Discussion

During 1993–2015, the regional spatial-temporal variation of urban-rural *NEHFC* showed dissimilar characteristics, which were primarily originated from distinct leading driving forces. It has been proved that per capita urban *NEHFC* was mainly affected by Regional Development Index (D) and Social-Economic level (S), while the rural *NEHFC* was driven by the combined actions of the three index groups including the Nature Geographic Index (G).

Although the dietary disparity between North-south resident in China has influenced the large-scale regional disparity of the urban *NEHFC*, the local development level and living standard of the provinces (cities) contribute to the increasingly higher *NEHFC* in the south of China, especially the south-eastern coastal developed provinces, as well as Beijing and Tianjin, than that in the rest regions. Residents in the above areas were more likely to accept food consumption model with high nitrogen content. In recent years, development advantage in southeast coastal areas has been diffused into Chinese hinterland, resulting in an improvement in the social-economic level of residents located in the middle part, especially for the people in the 'T' (Middle) areas. However, the growth rate of *NEHFC* at the 'T' (Middle) area was higher than that in the other provinces. This may be explained by relatively incomplete *Nr* recycling utilization mechanism and less attention to the healthy diet compared with the coastal developed regions. Although the 'North-South' disparity showed the effect of Nature Geographic Index (G) on *NEHFC* to some extent, the phenomenon, however,was gradually weakened during the study period. Due to the continuous deepening of China's reform and opening-up policy, the impact of interregional trade on the urban resident dietary structure may also increase and even surpass the control power of the geographical boundary.

Regional Development Index (D) and Social-Economic Index (S) posed an apparent impact on the formation of the regional spatial-temporal variation of per capita rural *NEHFC*. This could be proved by the fact that the hotspot of provincial per capita rural *NEHFC* concentrated in the Southeast of mainland China. Nevertheless, the influence of Nature Geographical Index (G) should not be neglected. Grain consumption still dominated the household food consumption of the rural resident in the nationwide. and it has dramatically reduced in recent years (Xi and Oyang 2016). However, The geographically driven rural daily dietary of Tibet, Inner Mongolia and three northeast provinces(Liaoning, Jilin, Heilongjiang) were not shocked dramatically as the other regions by the downtrend in grain consumption. The residents in Western China, such as Tibet, Xinjiang and so on, consume more animal-based food in daily dietary than those in the rest areas. it primarily due to the geographically driven regional dietary characteristics, such as climate, altitude, religion,natural background value and so on, resulting in the variation rates of Western China not so sensitive as the Middle and Eastern parts under the noticeable reduction of grain consumption. Most provinces in Middle and Eastern China experienced a faster decreasing in per capita rural *NEHFC*. However, several eastern developed areas, such as Beijing, Tianjin, Shanghai, Fujian, and Guangdong, presented different local spatial-temporal variation patterns compared with the neighbor provinces in Middle-Eastern China, especially after 2000. It reflected that the restrictions brought by nature geography environment on household food consumption were gradually broken.

Furthermore, the impact of Regional Development Index (D) exhibited significant fluctuation both in the urban and rural *NEHFC*, with Social-Economic Index(S) becoming the dominant factor in a different period. It indicated that the impact of the Social-Economic index (S) on *NEHFC* had a more specific time lag than the regional development. It provided us with an opportunity to control the *NEHFC* while maintaining the regional development. Therefore, the reasonable and balanced dietary structure should be encouraged along with the local development. Additionally, it is also essential to expand the use of new efficient waste disposal technologies and improve regional manure and waste management ability. Notably, the q values of Nature Geographic Index (G) showed a gradual decrease more recently. However, due to some large-scale geographical factors, North-South and East – Middle -West disparities still played a role in restraining spatial-temporal variation patterns of urban and rural *NEHFC*.

Conclusion

Based on the material flow and spatial-temporal analysis, our study discussed the spatial-temporal variation patterns of urban-rural *NEHFC* from 1993 to 2015 respectively, under the view of urban-rural and regional disparity in mainland China. Furthermore, their distinctive driving forces and the influence mechanism were also separately identified from the three groups indexes including Nature Geographical Index (G), Regional Development Index (D), and Social-economic Index (S).

Our results proved that (i) Increasingly apparent regional disparities were found in both the national spatial patterns of provincial per capita urban-rural *NEHFC* during 1993–2015. However, the national annually spatial autocorrelation pattern of urban *NEHFC* demonstrated a 'U' type, comparing with a decreasing *Moran's I* index on the variation of rural *NEHFC*. (ii) The regional spatial-temporal variation of per capita urban *NEHFC* exhibited 'South (High)-North (Low)-Middle (Fast)' trend, while the local spatial-temporal pattern of per capita rural *NEHFC* showed 'Belts' disparity. The hotspot of per capita rural *NEHFC* mainly concentrated in South-eastern China with a distinct regional changing of 'Middle-East (Fast) & west (Slow).' (iii) The Social-Economic and Regional-Development Index were far more critical than the Natural-Geographic Index on the spatial-temporal variation of per capita urban *NEHFC*, whereas the rural *NEHFC* was driven by the combined actions of all the three indexes above. Some large-scale geographical factors still played essential roles in the restraining spatial-temporal variation of urban-rural *NEHFC*, which, however, gradually weakened in recent years.

The available strategies for reducing the risk of *NEHFC* losses to the environment include implementing 'Location-Suitable' nitrogen management practices to reducing the regional disparities, and promoting 'urban-rural nitrogen recycling frame' to narrowing down the urban-rural differences. The regional differences of per capita *NEHFC* could be explained by the unbalanced regional development and social-economic growth. Thus, the urban *NEHFC* in the southern provinces and the rural *NEHFC* in south-eastern China should be highlighted. Moreover, the urban *NEHFC* of several 'Middle' ('T') provinces in mainland China and rural *NEHFC* in several particular changing regions (e.g. Beijing, Guangdong, Shanghai) should also be taken into serious consideration. The reasonable and balanced dietary structure is desperately encouraged in above areas. Moreover, enhancing *Nr* recycling utilization mechanism is also crucial for these emerging regions. Urban systems block the *NEHFC* from re-entering the agro-ecosystem, resulting in less nitrogen is recycled in urban areas than that in rural areas (Wei et al. 2008; Lin et al. 2014). Therefore, a better strategy is to promote an 'urban-rural nitrogen recycling frame' for increasing the recycling *Nr* rates in the urban area. In other words, cities provide the technique and financial support to encourage 'Modern Agriculture' in a rural area. The rural part utilizes the urban kitchen waste as livestock feeding and urban human excrement as farming fertilizer. The method is helpful not only to offset the lower recycling utilization of urban nitrogen after household food consumption but also to close the *N* cycle between urban and rural areas. Furthermore, awareness enhancement and public involvement are also conducive. Relevant authorities and agencies should carry on the work of waste management and nitrogen emission controlling by an in-depth understanding of the local characteristics as well as the serious consideration of cross-boundary corporation.

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