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What Determines China's Agricultural Nonpoint Source Pollution? An Improved LMDI Decomposition Analysis

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Using the logarithmic mean Divisia index method, this paper decomposes changes in China's agricultural nonpoint source pollution into five factors: emission intensity, production scale, labor intensification, urbanization, and population-scale factors. Moreover, we further explore the contribution of each factor at different agricultural policy stages and the impact of subsidies on emissions. Our main findings show that emission intensity is the main restraining factor of pollution, while production scale plays the greatest effect on aggravating loads. The incentive effect of agricultural subsidies reduces emissions, but the expansion of government fiscal expenditures will lead to an increase.

Key words: agricultural policy, agricultural pollution, influence factors, subsidy effect

Introduction

China's agriculture has experienced rapid development since the implementation of the Reform and Opening-up Strategy, following which China was able to feed 22% of the world's population using only 8% of the earth's cultivated land (Liu et al., 2020). Nevertheless, behind the bumper harvest, the agricultural sector was highly dependent on a large number of chemical production factors; in other words, prosperous agriculture was based on extensive development. From 2000 to 2016, China increased the amount of chemical fertilizers used by 44.33%, from 41.46 million tons to 59.84 million tons; over the same period, pesticide use rose by 35.94%. The intensive inputs promoted agricultural production, but they also increased agricultural nonpoint source pollution (ANSP) (Wang et al., 2019). As reported by the *First National Pollution Source Census Bulletin*, in the agricultural sector, chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP) in 2007 were 13.24 million tons, 2.70 million tons, and 0.28 million tons, respectively, accounting for 43.71%, 57.19%, and 67.27% of total pollution loads. Moreover, agriculture and livestock husbandry account for a larger portion of nonpoint source pollution than industry and living sewage (Zhang, Yu, and Hu, 2011).

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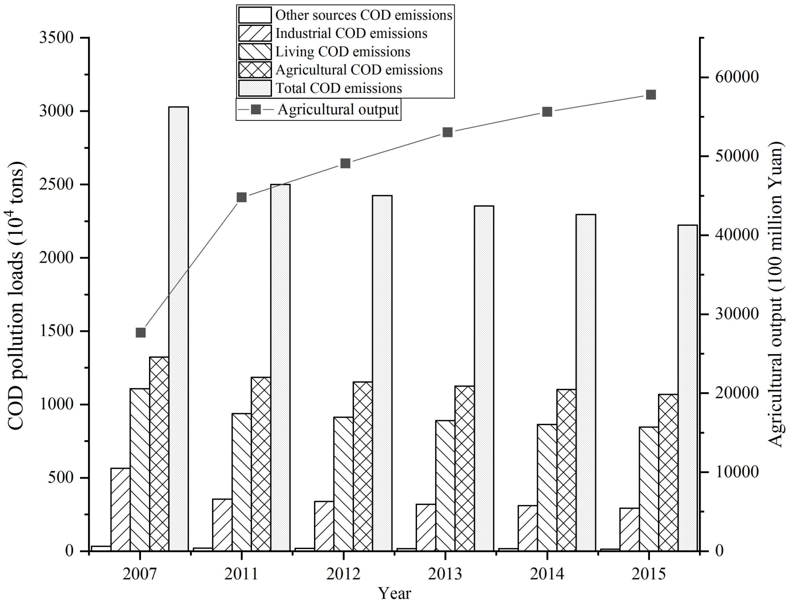

Figure 1. China's Agricultural Output and COD Pollution Loads in Major Years

Source: First National Pollution Source Census Bulletin (2010), *Environmental Statistics Annual Report*.

The prominent pollution problem has severely restricted sustainable development of the agricultural and socioeconomic environment. Therefore, the No. 1 Central Document focused on issues for ANSP in 2005. After that, many policies such as the *Action Plan for Tough Battle against Rural and Agricultural Pollution* have been put forward to deal with ecological and environmental issues in rural areas. Several unequivocal quantitative abatement targets have been set. For instance, China aimed to achieve zero growth in the use of fertilizers and pesticides by the year 2020 and to reduce TN and TP emissions from ANSP by more than 30% (The 13th Five-Year Plan for the Development of Agricultural Science and Technology, 2017). After a series of control measures, ANSP emissions began to improve, but the situation was still not optimistic. Figure 1 shows that given steady increases in agricultural output, the COD from agriculture decreased but was still at a high level and larger than from other sources. Specifically, COD emissions from industry declined by 17.28% and the overall COD emissions abatement rate was 11.06%, while agricultural COD emissions only fell by 9.91% from 2011 to 2015.

However, ANSP research has mainly focused on environmental aspects (Yi et al., 2021), rarely considering the economy-environment perspective. Furthermore, the influence factors behind ANSP variations have rarely been studied. To reduce pollution and improve the agricultural ecological environment, we must explore the drivers of the increase of ANSP emissions. In this paper, we use an inventory analysis to evaluate China's ANSP emissions from 2000 to 2018 and apply the logarithmic mean Divisia index (LMDI) method to analyze the driving forces of ANSP to provide appropriate policies for green agricultural development.

Literature Review

Pollutant accounting is a prerequisite for implementing emission abatement strategies (Wang et al., 2016). In terms of agriculture pollutants, many studies have only concentrated on carbon emissions (Shen et al., 2018; Saravia-Matus, Aguirre Hörmann, and Berdegué, 2019), taking CO_2 as the sole measure of agricultural pollution loads and ignoring the severity of ANSP. However, measuring ANSP is challenging due to the lack of detailed and continuous data (Zou et al., 2020) and its characteristics of "uncertainty, concealment, difficulty in monitoring and high cost of data acquisition" (Shen et al., 2012). Several alternative methods have been applied to evaluate ANSP; these can be divided into model simulation used to estimate a certain area or basin, and inventory analysis from the perspective of agricultural elementary units (EUs). Considering the feasibility of the operation and the cost required, many estimation methods are not acceptable to measure overall ANSP in China. Inventory analysis is an inexpensive and manageable method that focuses on relative long-term and average pollution loads (Chen, Chen, and Du, 2006). Liu and Feng (2019) employed inventory analysis to calculate ANSP and considered it alongside carbon emissions as an undesirable output to assess China's agricultural green productivity. Zou et al. (2020) then adopted this method to assess ANSP loads in China from 1978 to 2017, and the results were reasonable. Therefore, the core parameters with Chinese characteristics and inventory analysis are applied to estimate China's ANSP accurately.

It is crucial to realize the driving forces of variation in ANSP to find attainable agricultural mitigation pathways. Accordingly, another strand of literature discusses socioeconomic influence factors of ANSP by employing either empirical regression models or decomposition models. Most studies using regression models have only considered one or two factors to analyze their effects on ANSP (Lu and Xie, 2018; Jiang et al., 2019). Nevertheless, the impact mechanism of environmental pollution changes cannot be entirely clarified by a single or small number of interactions (Xia et al., 2020). Decomposition analyses are generally separated into structural decomposition analysis (SDA), production-theoretical decomposition analysis (PDA), and index decomposition analysis (IDA). SDA is based on the input-output (I-O) framework and relies on large amounts of disaggregated data about final demand and input-output coefficients in I-O tables (Wang and Feng, 2021). Considering the availability of the annual I-O tables and the different policy periods examined in this research, the SDA approach is not applicable here. PDA can model general production processes to capture changes in technology and production efficiency (Chen et al., 2019), but this method lacks the additive decomposition form and mainly carries out the study from the perspective of production technology, so it cannot meet the purposes of this research.

Given the lower data requirement, comprehensible operation, and its availability at any level of aggregation, the IDA approach is suitable for more detailed temporal and spatial studies (Qian, Cao, and Huang, 2020). Ang, Zhang, and Choi (1998) proposed an IDA method, the logarithmic mean Divisia index (LMDI), which has been widely applied for its superiorities of decomposition without residual term and zero value, consistency, interpretability of results, and a simple and understandable relationship between the additive and multiplicative forms (Ang, 2004; Ang and Liu, 2007). This approach has been applied at the global level (Chen et al., 2020; Yang, Hao, and Feng, 2021), the national level (Quan et al., 2020), the provincial level (Xia et al., 2020), and the urban level (Zhang et al., 2019; Zheng, Wang, and Du, 2020). From the decomposed objects, it has been commonly used to analyze energy consumption (Jiang et al., 2020) and multiple types of pollutants (Zhang et al., 2019; Feng, Xia, and Sun, 2020; Qian, Cao, and Huang, 2020).

The LMDI method has also been applied in the agricultural sector. Wang et al. (2018) used the LMDI method to analyze factors influencing Chinese vegetable production. Zhang et al. (2018) took planting scale, production pattern, irrigation quota, and efficiency as representative factors to study the main driving forces of agricultural water use. Others have used the LMDI method to decompose changes in the amount and efficiency of agricultural chemical inputs (Yang and Lin, 2019; He et al., 2020). Discussion about decomposition factors of agricultural carbon emissions using the LMDI method has attracted popular attention. Liu and Feng (2021) extended the LMDI and PDA methods from structural and technical perspectives to identify the drivers of the decoupling between economic growth and CO_2 emissions in the agricultural industry. However, the importance of socioeconomic factor analysis of ANSP has been neglected. By decomposing the emergy flow of environmental impacts of nonpoint source pollution, Liu et al. (2021) concluded that economic factors played a contributing role, while intensity and technology factors had a restricting role. Furthermore, Zou et al. (2020) proposed that the driving mechanisms of ANSP loads will likely be concentrated in the future. Accurately grasping the contributions of different factors to changes in ANSP and its influencing mechanisms are the basis of pollution mitigation. Considering the characteristics and wide applicability of the LMDI method in the agricultural sector, it is appropriate to apply it to explore socioeconomic driving forces of ANSP.

On the whole, we can summarize the existing research as follows: (i) the temporal and spatial characteristics of ANSP in China have not been viewed in detail; (ii) studies on the influencing factors of agricultural pollutants mainly emphasize carbon emissions and do not consider ANSP, so cannot provide feasible pathways for reducing ANSP emissions; (iii) as the agricultural sector is heavily affected by government policies, the issue of NSP in the context of agricultural policy implementation is seldom discussed. To fill these research gaps and answer questions about the driving forces of changes in ANSP and the contributions of different factors, we perform a provincial-level inventory analysis to evaluate the spatial-temporal distribution of ANSP emissions and use the LMDI method to decompose socioeconomic factors from different regions at different developmental stages. We explore the driving mechanism in combination with the different agricultural policy periods, providing theoretical and empirical support for agricultural emissions mitigation.

Methodology

Estimating Agricultural Nonpoint Source Pollution Based on Inventory Analysis

Partly based on Lai, Du, and Chen (2004) and Chen, Chen, and Du (2006), the agricultural pollution sources in this research are divided into two types: First, ANSP emissions come from farmland production, (e.g., the loss of fertilizers, pesticides and plastic film, agricultural solid waste). Second, breeding—including livestock and poultry breeding and aquaculture—is also an important source of ANSP. Different from Lai, Du, and Chen (2004) and Chen, Chen, and Du (2006), our research emphasizes the pollution loads of the agricultural sector rather than rural nonpoint source pollution. This paper does not include rural household waste because it is not mainly caused by agricultural production.

For the comparability of various pollutants, we evaluate the major components of ANSP: total nitrogen (TN), total phosphorus (TP), and chemical oxygen demand (COD) (Zou et al., 2020). Combined with the "top-down" principle of inventory analysis, the relationship between agricultural activities and pollution loads can be demonstrated as

$$(1) \qquad ANSP = \sum EU_{activity} = \sum \sum EU_{class} = \sum \sum \sum EU_{unit} \times EUA,$$

where $ANSP$ is agricultural nonpoint source pollution emissions; $EU_{activity}$ is polluting activities in agricultural production; EU_{class} is composed of EU_{unit}, which shows pollution of agricultural class; and EU_{unit} represents the pollution loads of agricultural units. Table 1 provides a detailed inventory list. Additionally, EUA demonstrates the quantities of pollutants discharged by a single elementary unit, computed by

$$(2) \qquad EUA = \sum_i EU_i \rho_{ij} (1 - \eta_i) C_{ij} \left(EU_{ij}, S\right) = \sum_i PE_{ij} \rho_{ij} (1 - \eta_i) C_{ij} \left(EU_{ij}, S\right),$$

where EU_i is the data statistic of unit i; ρ_{ij} is the pollution generation coefficient of pollutant j in unit i; $\eta_{ij}$is the coefficient that expresses the resource's utilization rate; C_{ij} is the discharge coefficient of pollutant j in unit i, which is decided by unit i and spatial characteristics S; and PE_{ij} is the maximum emission of pollutant j in unit i without efficiency constraints.

LMDI Decomposition Approach

Combined with the mathematical identity, the LMDI method decomposes the target variable into several major factors to discover the influence of each factor on the research object (Wang et al.,

Table 1. Elementary Units of China's ANSP

Activity	Class	Unit	Indicator	Pollution
Fertilizer runoff	Nitrogenous fertilizer (NF)	NF of grain crops NF of vegetables NF of other crops	Fertilizer consumption (10^4 t)	TN, TP
	Phosphate fertilizer (PF)[a]	PF of grain crops PF of vegetables PF of other crops	Fertilizer consumption (10^4 t)	TN, TP
	Compound fertilizer (CF)	CF of grain crops CF of vegetables CF of other crops	Fertilizer consumption (10^4 t)	TN, TP
Livestock and poultry[b]	Livestock	Cow and cattle Pigs Sheep	Year-end total number (10^4 head) Slaughtered number (10^4 head) Year-end total number (10^4 head)	COD, TN, TP
	Poultry	Poultry	Slaughtered number (10^4 head)	
Agricultural solid organic waste	Grain crops	Rice Wheat Beans Corn	Output (10^4 t)	COD, TN, TP
	Cash crops	Peanuts Oil-bearing crops		
Aquaculture	Sea	Mariculture	Output (10^4 t)	COD, TN, TP
	River or lake	Freshwater aquaculture		

Notes: The abbreviations for chemical oxygen demand, total nitrogen and total phosphorus are TN, TP and COD, respectively.
[a] Pure consumption of phosphate fertilizer is the amount of P_2O_5. To get TP, we need to multiply by 43.67%.
[b] The year-end total number and slaughtered number depend on the growth cycle of livestock and poultry. Considering that the average feeding period for cattle and sheep is over 1 year, the year-end total number is used; pigs and poultry have average feeding periods of 180 days and 55 days, respectively, and so the slaughtered number is applied.

2018). Considering the unified framework of "environment-economy-population," the mathematical identity of factor decomposition is

$$(3) \quad NSP = \sum_{i}^{n} \frac{NSP_i}{Q_i} \times \frac{Q_i}{Cul_i} \times \frac{Cul_i}{Pop_{rur_i}} \times \frac{Pop_{rur_i}}{Pop_i} \times Pop_i = \sum_{i}^{n} Int_i \times Sca_i \times Percul_i \times Iu_i \times Pop_i,$$

wherein NSP is ANSP emissions; Q_i is agricultural output, expressed by the output of primary industry; Cul_i is cultivated land, represented by the total agricultural area sown; and Pop_{rur_i} and Pop_i represent the rural and total population, respectively. In model (3), the driving forces of ANSP emissions can be decomposed as emission intensity ($Int_i = \frac{NSP_i}{Q_i}$); scale of agricultural economy ($Sca_i = \frac{Q_i}{Cul_i}$); rural per capita cultivated land resource ($Percul_i = \frac{Cul_i}{Pop_{rur_i}}$), which shows the inverse labor intensification (Yang and Lin, 2019); and indirect urbanization level ($Iu_i = \frac{Pop_{rur_i}}{Pop_i}$), which is the inverse of urbanization level.

In particular, emission intensity has an important effect on pollution emissions, and its decrease means the reduction of pollution per unit of agricultural output. Optimizing emission intensity is a potent path to achieving abatement (Zhang et al., 2019). Agricultural output per unit of cultivated land will have a scale effect on pollution loads. As shown above, the per capita cultivated land resource can be regarded as the inverse of labor intensification. For this factor, the substitution effect of agricultural labor for chemical inputs will alter agricultural production patterns (Yang and Lin, 2019) and change emissions. In addition, urbanization is a fundamental way to solve the contradiction of China's dual economic structure and a vital variable of economic prosperity (Liu and Feng, 2020). Urbanization will drive the transfer of the rural labor force and affect agricultural mechanization levels, which will lead to changes in ANSP. The last factor, population, is regarded as a fundamental factor for emissions.

Based on the principle of LMDI additive decomposition, we decompose changes in ANSP into the variation of five factors:

$$NSP^T - NSP^0 = \Delta NSP_{Tot} = \Delta NSP_{Int} + \Delta NSP_{Sca} + \Delta NSP_{Percul} + \Delta NSP_{Iu} + \Delta NSP_{Pop}, \tag{4}$$

where NSP^T and NSP^0 denote NSP in period T and the base period, respectively. The variation of each factor can be calculated as

$$\Delta NSP_{Int} = \sum_i^n \frac{NSP_i^T - NSP_i^0}{\ln NSP_i^T - \ln NSP_i^0} \ln\left(\frac{Int_i^T}{Int_i^0}\right); \tag{5}$$

$$\Delta NSP_{Sca} = \sum_i^N \frac{NSP_i^T - NSP_i^0}{\ln NSP_i^T - \ln NSP_i^0} \ln\left(\frac{Sca_i^T}{Sca_i^0}\right); \tag{6}$$

$$\Delta NSP_{Percul} = \sum_i^N \frac{NSP_i^T - NSP_i^0}{\ln NSP_i^T - \ln NSP_i^0} \ln\left(\frac{Percul_i^T}{Percul_i^0}\right); \tag{7}$$

$$\Delta NSP_{Iu} = \sum_i^n \frac{NSP_i^T - NSP_i^0}{\ln NSP_i^T - \ln NSP_i^0} \ln\left(\frac{Iu_i^T}{Iu_i^0}\right); \tag{8}$$

$$\Delta NSP_{Pop} = \sum_i^n \frac{NSP_i^T - NSP_i^0}{\ln NSP_i^T - \ln NSP_i^0} \ln\left(\frac{Pop_i^T}{Pop_i^0}\right). \tag{9}$$

To explore the extent of certain factors' contributions to ANSP emissions, we define the contribution rate, Cr, as

$$\begin{aligned} Cr_{Tot} &= \frac{\Delta NSP_{Int} + \Delta NSP_{Sca} + \Delta NSP_{Percul} + \Delta NSP_{Iu} + \Delta NSP_{Pop}}{\Delta NSP_{Tot}} \\ &= Cr_{Int} + Cr_{Sca} + Cr_{Percul} + Cr_{Iu} + Cr_{Pop}. \end{aligned} \tag{10}$$

Data Sources

To investigate the spatial-temporal characteristics of changes in China's ANSP emissions and each factor from 2000 to 2018, we divide 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan due to the availability and consistency of data) into four regions.[1]

The elementary unit data used to calculate ANSP come from *China Rural Statistical Yearbook* (2000–2018), *China Fishery Statistical Yearbook* (2000–2018), and *China Marine Statistical Yearbook* (2000–2018). The pollution generation coefficients and discharge coefficients of various

[1] The eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The northeast region includes Liaoning, Jilin, and Heilongjiang.

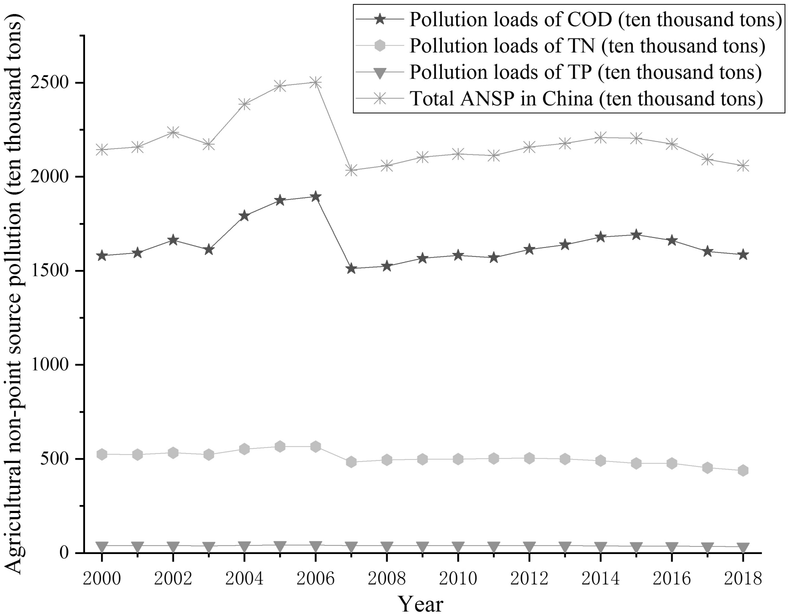

Figure 2. Total Pollution Loads of Agricultural Nonpoint Source Pollution in China, 2000–2018

pollutants (mentioned in equation 2) originate from the *First National Pollution Source Census Bulletin*, and the experimental parameters like the resource's utilization rate and maximum discharge of pollutants are derived from Lai, Du, and Chen (2004) and Chen, Chen, and Du (2006). Data on agricultural output and cultivated land come from the *China Rural Statistical Yearbook* (2000–2018). Agricultural output is expressed as the added value of the primary industry, which we adjust into constant prices based on the year 2000 to eliminate the influence of price fluctuations. Total and rural population come from the *China Population and Employment Statistical Yearbook* (2000–2018).

Empirical Results

Agricultural Nonpoint Source Pollution in China

We estimate China's ANSP from 2000 to 2018 using an inventory analysis. To verify accuracy, we compared our results against data published in the *First National Pollution Source Census Bulletin*. Our results are bigger than the statistical data in the *First National Pollution Source Census Bulletin*, which covers only part of the typical agricultural operation area rather than the whole of China. Meanwhile, our results are smaller than those reported by Lai, Du, and Chen (2004) and Zou et al. (2020) because this research excludes pollution caused by rural life and only considers agricultural production. However, the total pollution trends are identical to these results and conform with reality.

Our results for total time trends are almost similar to Zou et al. (2020), as shown in Figure 2. After increasing from 2000 to 2002, ANSP loads declined slightly from 2003, climbed to a peak in 2006, exceeding 25 million tons, then declined sharply and reached a nadir in 2007. However, it started to rise again from 2008 to 2014 and gradually fell until 2018.

Livestock produced the largest amount of pollution, followed by agricultural solid waste, then aquaculture and fertilizer runoff (see Figure 3). By comparing Figures 3(a) and 3(b), it is clear that the pollutant emissions ratio of livestock remained stable at 86% in both 2000 and 2018, whereas the emissions ratio from agricultural solid waste fell from 10.45% to 7.30% and the proportion of

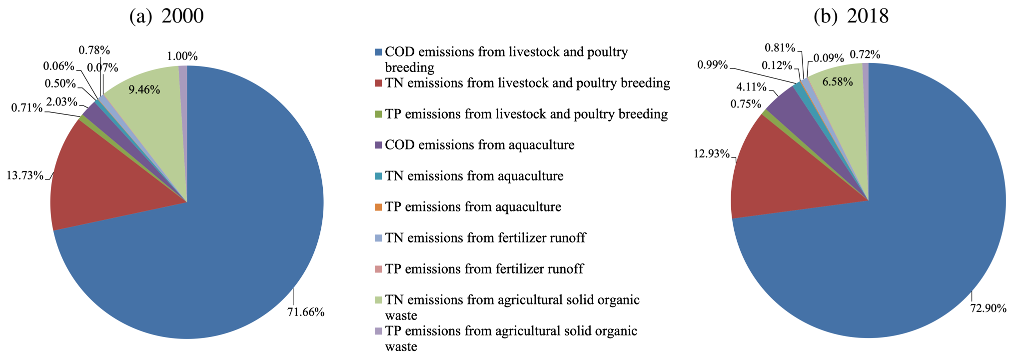

Figure 3. Main Sources of ANSP Emissions, 2000 and 2018

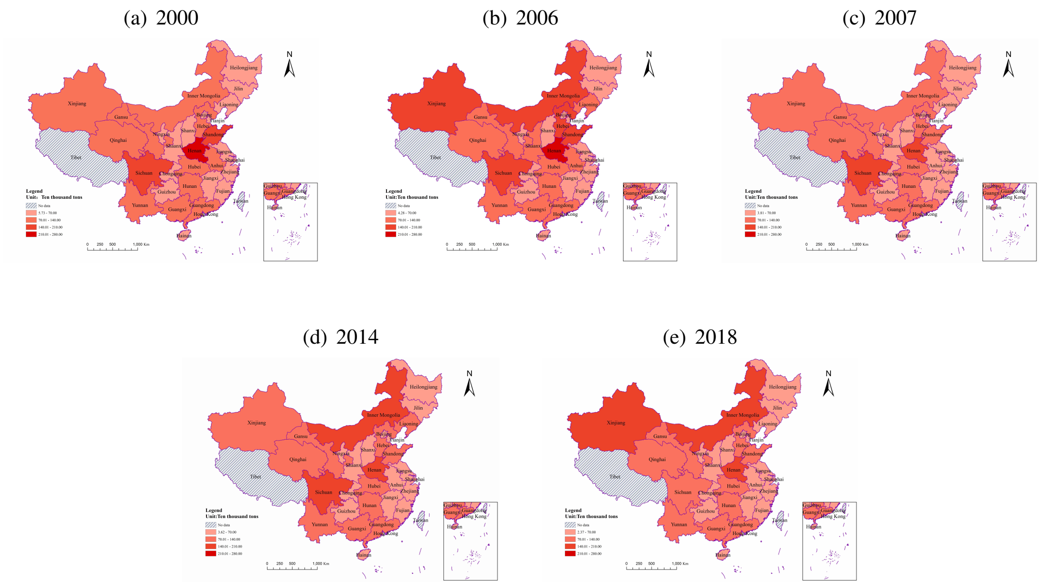

Figure 4. ANSP Emissions in China over Time

pollution produced by aquaculture rose. Livestock produces the largest nonpoint source pollution in agriculture (Zhang et al., 2019, p. 66) and is characterized by "large scale, concentrated emissions and difficult to control." Moreover, a large number of COD emissions are also derived from it. Conversely, due to the extension of a pilot program for recycling agricultural waste and the development of an agricultural waste resources market (e.g., the straw market), the utilization rate of agricultural solid waste increased year by year. The straw utilization rate exceeded 82% in 2007, and the nonpoint source pollution generated showed a downward trend.

Figure 4 plots the ANSP of each province at the beginning (2000), end (2018), and turning points (2006, 2007, and 2014) based on the characteristics of ANSP changes during the study period. The southeast coastal region has always maintained "low pollution," related to its industrial structure and technical level. Eastern China is a leader in green agricultural development (Liu and Feng, 2019). The northeast region also nearly remains at "low pollution," except for Liaoning in 2006 and 2014. However, the western region is mostly dominated by "middle-high pollution" and "high pollution" areas, and various levels of pollution have appeared in the central region. Henan, a major agricultural province, is in the "middle-high pollution" and "high pollution" levels, indicates massive waste and unreasonable use of resources (Li et al., 2018). Only three provinces were at the "middle-high

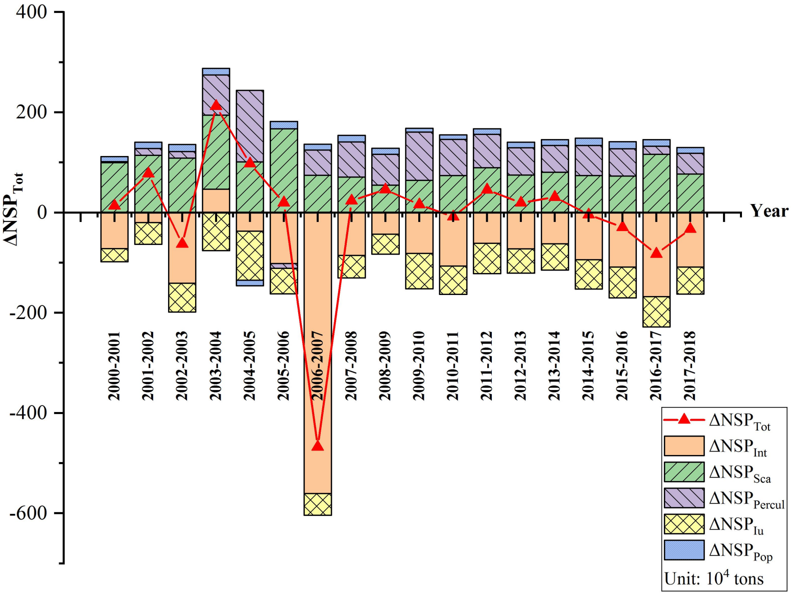

Figure 5. Annual Decomposition Results of China's ANSP

pollution" level or above in 2000, this number doubled in 2006 but then dropped to two in 2007, and finally returned to three. Sichuan was at the "middle-high pollution" state at four points but dropped to "middle-low pollution" in 2018. Due to the large scale of their livestock sectors, Xinjiang and Inner Mongolia are the provinces with more serious nonpoint source pollution.

Decomposition Results of Agricultural Nonpoint Source Pollution

Table 2 reports the annual decomposition results of ANSP and the contribution of each factor from 2000 to 2018. As shown in Figure 5, the emission intensity effect is negative every year except from 2003 to 2004, which indicates this factor inhibits ANSP emissions. As emission intensity is the reciprocal of emission efficiency, decreasing emission intensity and increasing efficiency will reduce ANSP. The emission intensity effect was the largest among the contribution rates of five factors in the eight annual intervals, demonstrating that the intensity effect played a dominant role in most years. From 2006 to 2007, it caused a significant drop, reducing ANSP emissions by 5.6066 million tons. As a great success of reform and opening up, the abolition of the agricultural tax in 2006 alleviated the distortion of factor constraints, stimulated the vitality of agricultural product markets and increased farmers' income (Yu and Jensen, 2010) to make agricultural production more efficient, and reduced ANSP emissions.

The scale effect of agricultural production on ANSP emissions is positive, illustrating that changes in the scale of agricultural production aggravate ANSP emissions each year. The expansion of agricultural land caused by continuous growth of the agricultural operation scale has made ANSP emissions increasingly serious (Ouyang et al., 2014). Indeed, the scale effect was the leading force behind ANSP emissions seven times during the study period. The labor intensification effect, which similarly increases the emissions, is also positive, except from 2005 to 2006. As a result

Table 2. Annual Decomposition Results of China's ANSP

	Changes in ANSP Emissions (10^4 tons)						Contribution Rate of Each Factor (%)				
Time Interval	ΔNSP_{Int}	ΔNSP_{Sca}	ΔNSP_{Percul}	ΔNSP_{Iu}	ΔNSP_{Pop}	ΔNSP_{Tot}	NSP_{Int}	NSP_{Sca}	NSP_{Percul}	NSP_{Iu}	NSP_{Pop}
2000–2001	−72.06	99.71	1.85	−26.21	10.31	13.61	−529.44	732.62	13.62	−192.57	75.78
2001–2002	−19.92	114.15	13.75	−43.31	12.76	77.44	−25.72	147.40	17.75	−55.92	16.48
2002–2003	−140.79	108.74	13.01	−57.77	14.16	−62.65	224.73	−173.58	−20.76	92.22	−22.60
2003–2004	46.88	147.60	80.28	−75.70	12.98	212.06	22.11	69.61	37.86	−35.70	6.12
2004–2005	−36.87	100.87	142.89	−97.79	−11.50	97.60	−37.78	103.35	146.41	−100.20	−11.78
2005–2006	−101.77	167.28	−9.56	−50.79	14.65	19.82	−513.39	843.90	-48.23	-256.21	73.92
2006–2007	−560.66	74.48	50.50	−43.40	11.60	−467.47	119.93	−15.93	−10.80	9.28	−2.48
2007–2008	−85.41	70.77	70.10	−44.88	13.05	23.62	−361.60	299.60	296.78	−190.01	55.24
2008–2009	−42.99	54.49	61.50	−39.86	12.57	45.71	−94.05	119.20	134.54	−87.20	27.50
2009–2010	−81.25	64.41	96.30	−70.77	7.30	15.99	−508.15	402.83	602.25	−442.61	45.68
2010–2011	−106.59	73.86	72.08	−56.53	8.93	−8.26	1,290.83	−894.38	−872.87	684.52	−108.10
2011–2012	−61.27	89.69	66.61	−60.37	10.90	45.57	−134.44	196.82	146.17	−132.47	23.93
2012–2013	−72.48	74.84	54.55	−48.20	10.88	19.59	-369.94	381.99	278.42	−246.01	55.53
2013–2014	−62.14	80.20	53.65	−52.46	11.63	30.89	−201.18	259.66	173.70	−169.84	37.66
2014–2015	−94.26	73.70	60.08	−58.44	14.68	−4.23	2,228.81	−1,742.76	−1,420.66	1,381.77	−347.16
2015–2016	−108.47	72.73	54.48	−61.88	14.00	−29.14	372.29	−249.62	−186.98	212.38	−48.06
2016–2017	−167.87	116.47	15.77	−60.26	13.27	−82.61	203.21	−141.00	−19.09	72.94	−16.06
2017–2018	−108.89	77.09	40.94	−53.95	11.91	−32.90	330.97	−234.31	−124.44	163.99	−36.21

Table 3. Cumulative Effect Decomposition Results of ANSP by Region, 2000–2018

	Changes in ANSP Emissions (10^4 tons)					
Region	ΔNSP_{Int}	ΔNSP_{Sca}	ΔNSP_{Percul}	ΔNSP_{Iu}	ΔNSP_{Pop}	ΔNSP_{Tot}
Nationwide	−1, 787.09	1, 571.49	885.05	−947.17	192.38	−85.35
East	−446.97	405.56	140.63	−292.73	75.73	−117.78
Central	−523.41	391.08	247.34	−253.85	25.81	−113.03
West	−712.62	672.07	404.05	−353.85	88.76	98.42
Northeast	−104.09	102.77	93.02	−46.75	2.08	47.04

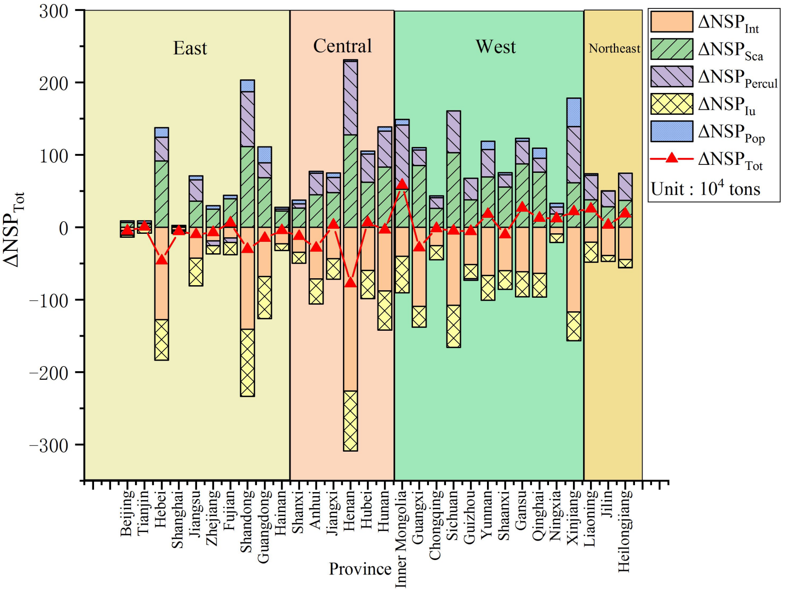

Figure 6. Decomposition Results of ANSP at the Provincial Level in China, 2000–2018

of the extension of agricultural land and the reduction of rural population caused by the improvement of urbanization, per capita cultivated land resource has escalated. Labor intensification can be expressed by the reciprocal of per capita arable land; when it drops, the degree of agricultural intensification declines (Yang and Lin, 2019), further leading to an increase in pollution.

The indirect urbanization factor is always below the horizontal axis of Figure 5, showing that indirect urbanization has reduced the ANSP emissions; from 2003 to 2004, indirect urbanization was the only factor inhibiting ANSP emissions. With the improvement of urbanization and the development of industrialization, the industrial structure has adjusted at the same time, reducing agricultural pollution. The last factor, population scale, also contributes to a rise in ANSP emissions. However, unlike the previous four factors, it has only a relatively small effect on ANSP changes; this result is similar to many studies on the impact of population size on agricultural carbon emissions (Chen, Cheng, and Song, 2018).

To clarify the total contribution share of each factor on ANSP emissions nationwide and in four regions, we performed the cumulative effect decomposition. Table 3 reports the results. During the study period, nationwide ANSP fell by 85.35×10^4 tons; the highest decline was 117.78×10^4 tons in the eastern region, followed 113.03×10^4 tons in the central region. However, ANSP in the west and northeast increased by 98.42×10^4 tons and 47.04×10^4 tons, respectively. For each region, the emission intensity effect is the most powerful driver for curbing ANSP emissions, while the scale of agricultural production is the strongest factor for increasing loads. In the western region, the emission intensity effect plays the greatest mitigating role but is not sufficient to counteract the

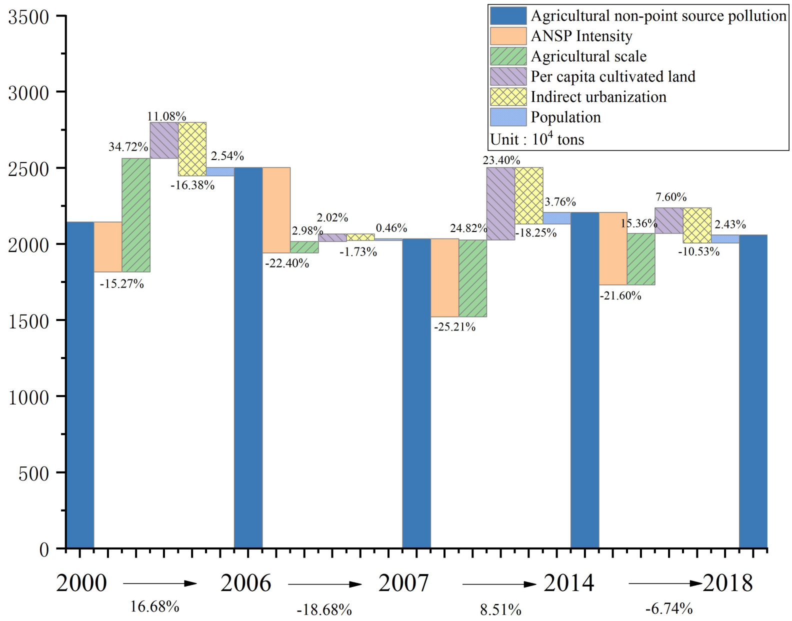

Figure 7. Contributions to Changes in China's ANSP Emissions over Time

pollution increment caused by scale effect and labor intensification effect. The eastern region, as the leading economic development area in China, has benefited from the adjustment and upgrading of the industrial structure. Its ANSP emissions increased by agricultural scale and labor intensification effects are only 4.0556 million tons and 1.4063 million tons, respectively.

The ANSP changes are further decomposed to the provincial level to explore the influence degree of various factors in different provinces (Figure 6). The factors of several major agricultural provinces (e.g., Henan, Shandong, and Hebei) and large-scale livestock provinces (e.g., Xinjiang and Inner Mongolia) changed greatly. For developed cities (e.g., Tianjin, Shanghai, and Beijing), the changes in factors are slight. The ANSP emissions eventually diminished in 17 provinces and were aggravated in the remaining 13 provinces, most of them in the western and northeast regions. Specifically, Henan is the province with the largest absolute reduction in the total amount of ANSP emissions, and its abatement brought by the intensity effect and indirect urbanization exceed the other three factors. However, as the province with the largest emission increment, Inner Mongolia has increased its per capita cultivated land resources, which is related to its own endowment characteristics. Declining labor intensification will lead to extensive agricultural development.

Driving Forces of Agricultural Nonpoint Source Pollution in Different Periods

Combining the changes in China's ANSP emissions and the implementation of agricultural policies, the study period is divided into four periods to further discuss the main factors affecting the whole country and regions at different stages and their contributions and mechanisms. The results are displayed in Figure 7 and Table 4.

China's ANSP emissions increased by 16.68% from 2000 to 2006, decreased by 18.68% from 2006 to 2007, increased by 8.51% between 2007 and 2014, and decreased by 6.74% between 2014 and 2018 (see Figure 7). The dominant factor in the first period (2000–2006) was agricultural scale. This is in line with the "large-scale and extensive" agricultural development pattern generally adopted in the early part of the twenty-first century to increase agricultural output. In the second period (2006–2007), the intensity effect was the strongest factor, reducing pollution. Agricultural

Table 4. Decomposition Results of Driving Forces of ANSP Emissions

Region	Time Interval	Changes in ANSP Emissions (10^4 tons)						Contribution Rate of Each Factor (%)				
		ΔNSP_{Int}	ΔNSP_{Sca}	ΔNSP_{Percul}	ΔNSP_{Iu}	ΔNSP_{Pop}	ΔNSP_{Tot}	NSP_{Int}	NSP_{Sca}	NSP_{Percul}	NSP_{Iu}	NSP_{Pop}
Nationwide	2000–2006	−327.45	744.64	237.58	−351.40	54.52	357.88	−91.50	208.07	66.38	−98.19	15.23
	2006–2007	−560.66	74.48	50.50	−43.40	11.60	−467.47	119.93	−15.93	−10.80	9.28	−2.48
	2007–2014	−513.16	505.04	476.19	−371.48	76.52	173.11	−296.43	291.74	275.07	−214.58	44.20
	2014–2018	−477.08	339.25	167.87	−232.48	53.56	−148.87	320.46	−227.88	−112.76	156.16	−35.98
East	2000–2006	−88.29	211.74	72.09	−160.75	29.52	64.31	−137.29	329.27	112.10	−249.97	45.90
	2006–2007	−157.98	21.57	0.71	−8.94	6.07	−138.57	114.01	−15.57	−0.51	6.45	−4.38
	2007–2014	−124.17	112.72	68.70	−86.84	31.23	1.64	−7,574.24	6,875.57	4,190.79	−5,297.36	1,905.24
	2014–2018	−98.15	90.33	5.81	−56.61	13.47	−45.15	217.39	−200.06	−12.86	125.37	−29.83
Central	2000–2006	−102.39	190.47	71.02	−85.85	−1.59	71.66	−142.89	265.82	99.11	−119.81	−2.22
	2006–2007	−188.21	14.68	20.28	−13.87	0.19	−166.95	112.74	−8.79	−12.14	8.31	−0.11
	2007–2014	−99.34	124.65	127.29	−100.42	13.94	66.12	−150.24	188.52	192.52	−151.89	21.08
	2014–2018	−160.91	86.60	44.60	−65.82	11.67	−83.86	191.88	−103.27	−53.19	78.50	−13.92
West	2000–2006	−124.12	289.29	60.94	−84.80	24.42	165.73	−74.89	174.55	36.77	−51.17	14.73
	2006–2007	−193.77	36.50	24.92	−19.46	4.74	−147.07	131.75	−24.82	−16.95	13.23	−3.22
	2007–2014	−244.25	216.17	241.73	−160.83	29.20	82.02	−297.80	263.56	294.72	−196.10	35.60
	2014–2018	−176.01	155.44	88.26	−100.91	30.96	−2.26	7,791.75	−6,881.16	−3,907.07	4,466.99	−1,370.52
Northeast	2000–2006	−12.65	53.14	33.53	−20.00	2.18	56.19	−22.52	94.57	59.67	−35.60	3.88
	2006–2007	−20.70	1.73	4.60	−1.12	0.60	−14.88	139.07	−11.64	−30.88	7.50	−4.05
	2007–2014	−45.40	51.51	38.47	−23.37	2.14	23.34	−194.55	220.69	164.82	−100.15	9.19
	2014–2018	−42.01	6.88	29.20	−9.14	−2.54	−17.61	238.58	−39.10	−165.85	51.93	14.44

scale, labor intensification, and population effects contributed 24.82%, 23.40%, and 3.76% of emissions, respectively, which were stronger than the intensity effect and indirect urbanization factor in the third period (2007–2014). In the fourth period (2014–2018), the combined influence of the two inhibiting factors was stronger than the influence of the three promoting factors. Therefore, the rationality of agricultural production scale and intensive development should be focused on.

Reducing Agricultural Tax and Establishing the Four Agricultural Subsidies, 2000–2006

At this stage, ANSP in all regions increased; the largest increase was in the western region, followed by the central region. This increase was mainly caused by continuous expansion of scale due to the urgent need for development of the agricultural economy, especially in the eastern region, where the contribution of the scale effect reached 329.27%. The pollution emissions growth in all regions indicates that the extension of agricultural scale and population size and the decline in labor intensification were stronger than the remaining two factors.

The most restraining factor of emissions in the central and western regions was intensity effect, which decreased by 1.0239 million tons and 1.2412 million tons, respectively, and contributed −142.89% and −74.89%, respectively. However, in the eastern and northeastern regions, the urbanization factor was the most restraining, abating 1.6075 million tons and 0.2 million tons, respectively, with a contribution rate of −249.97% and −35.60%, respectively.

Since the State Council issued its *Notice on the Pilot Reform of Rural Taxes and Fees* in 2000, the Chinese government has continuously increased the pilot provinces and established agricultural subsidies.[2] Meanwhile, the promulgation and implementation of the Agricultural Mechanization Promotion Law in 2004 marked a new era for China's agricultural mechanization. Supported by policies, the rapid advancement of mechanization has not only liberated the labor force but also improved efficiency and effectively reduced pollution. However, urbanization dominated the eastern region's mitigation at this stage because economic urbanization had the most significant impact on rural development in the early part of the period in the eastern and southeastern coastal areas (Feng, Liu, and Qu, 2019). In detail, economic urbanization improves the agricultural environment by boosting labor productivity and technological progress.

Completely Abolishing Agricultural Taxes, 2006–2007

During this period, a milestone in agricultural development occurred: The agricultural tax that had existed in China for more than 2,600 years was completely abolished. In terms of emission reduction, the contribution rate of intensity effect in all regions was greater than that of urbanization. Driven by the emission intensity factor, the national ANSP had decreased by 5.6066 million tons, including 1.9377 million tons in the west, 1.8821 million tons in the central region, 1.5798 million tons in the east, and 0.207 million tons in the northeast. Following the abolition of agricultural tax and the implementation of various agricultural subsidies, advances in agricultural technology and machinery led to agricultural green development, and the reduction effect brought by emission intensity became greater.

Conversely, for the emission promotion factor, the labor intensification effect in northeast and central regions at this stage had been larger than the scale effect of agricultural production. As urbanization attracted large numbers of rural populations into cities, the shortage of rural labor force and the growth of rural per capita arable land resources increased the burden on the environment and the resources waste.

[2] The government established three kinds of agricultural subsidies in 2004—(i) direct subsidies for grain, (ii) subsidies for improved varieties, and (iii) subsidies for agricultural machinery and tools—and increased the comprehensive subsidies for agricultural materials in 2006.

Improving the Price Protection Level and Subsidy Level, 2007–2014

The main features of China's agricultural policy from 2007 to 2014 were a boost in the level of price protection for agricultural products and the intensity of agricultural production subsidies. ANSP emissions increased by 1.7311 million tons nationally, with the largest increase (0.8202 million tons) in the western region, with a decreasing trend from west to east. The inhibition and promotion factors in the east were almost balanced, leading ANSP to increase by only 16,400 tons. The largest promotion factor in the east and northeast was the agricultural scale; however, in the central and western regions labor intensification was the largest promotion factor, with contribution rates of 192.52% and 294.72%, respectively.

The government had raised the minimum purchase price of wheat and rice since 2008, and by 2014 the price of wheat had increased by 64%. At the same time, agricultural film, feed, fertilizers, pesticides, etc. were exempt from value-added taxes. By increasing agricultural product prices through a "fast run by small step" way to further stimulate the expansion of agricultural scale, however, pollution increased. Our results show that the contribution of agricultural scale was highest in this particular stage, and the central and western regions had lower labor intensification than the east, leading to higher emissions.

Controlling Prominent Problems in the Agricultural Environment, 2014–2018

Between 2014 and 2018, ANSP in all regions decreased, and the intensity effect was the leading factor in reducing emissions. With the deepening of agricultural informatization and mechanization, the level of agricultural technology in the east was relatively high, while the western region had great potential for abatement. During this period, the application of agricultural science and technology promoted sustainable development. However, with the exception of the northeast region, the promoting factors were all dominated by the agricultural scale factor. The scale effect of population was also becoming increasingly obvious, especially in the east, where the contribution rate of this factor exceeded that of labor intensification. Unlike previous periods, population size had become the constraint on ANSP emissions in the northeast.

The central government has allocated special funds to improve the quality of farmland and the utilization of organic fertilizers and straw since 2014. *Establishing a Green Eco-Oriented Agricultural Subsidy System Reform Plan* was put forward in 2016, indicating that the government focused on solving the problems of agricultural pollution. It can be seen from the results that the emission intensity has greatly reduced ANSP emissions. Meanwhile, with the continuous improvement of the intensification degree, the strength of this factor to increase pollution gradually became weaker and the contribution rate of the eastern region was only 12.86%. Similar to the impact of population size on agricultural carbon emissions (Zhao et al., 2018), population expansion will undoubtedly contribute to ANSP loads. However, the population of the northeast decreased over time, from 109.76 million in 2014 to 108.36 million in 2018. In this case, the pollution from the agricultural sector was relatively diminished.

Discussion

The fiscal policies of China's agriculture had undergone transformations from tax collection to tax reduction and three kinds of agricultural subsidies then to the tax-for-free and expansion of subsidies scope. It is worth discussing how influencing factors impact ANSP emissions under the background of these transformations. Tax and subsidy (part of the financial expenditure) are two efficacious ways to control agricultural pollution (Chen et al., 2017). Abman and Carney (2020) proposed using taxes and subsidies in food production to improve environmental quality. So, how do the incentive effect of agricultural subsidies and financial support affect agricultural pollution? To find the answer, the

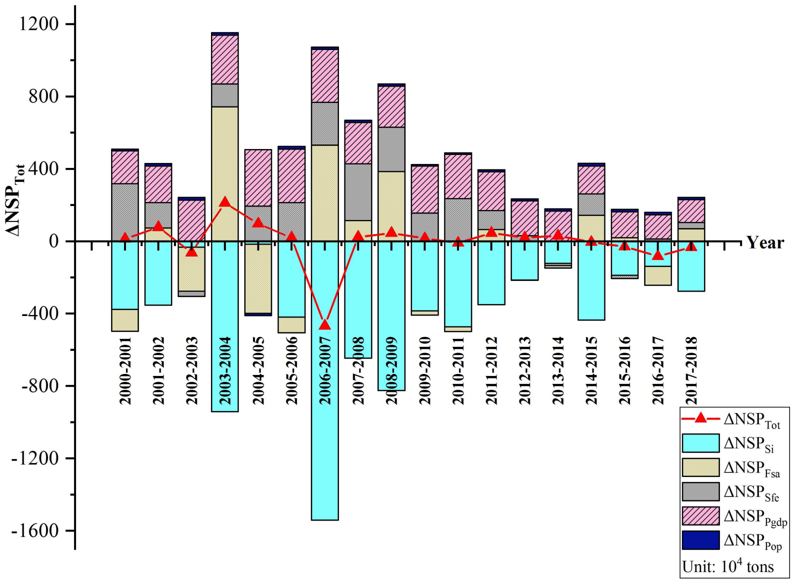

Figure 8. Annual Decomposition Results of China's ANSP Emissions Based on Agricultural Policies

LMDI method is used from the perspective of policies, and the specific decomposition formulas and results are shown in the appendix.

In the context of tax abatement and enhanced yield subsidies, farmers' labor enthusiasm was inspired to increase agricultural production; meanwhile, the relatively lagging development of agricultural technology in the early period increased pollution (Yu and Jensen, 2010). This was most obvious at the first stage of tax reform (2000–2006), when the agricultural scale in each region took the leading position, with the highest contribution rate (329.27%) in the eastern region. Total agricultural support increased from 23,180.58 million USD to 55,605.57 million USD in this period (Organisation for Economic Co-Operation and Development, 2022). The incentive effect of agricultural subsidies clearly reduced ANSP emissions (see Figure 8). Moreover, changes in ANSP emissions, especially the reduction of 3.8193 million tons between 2004 and 2005, depended on the strength of agricultural financial support. For the sharp drop in 2006, the incentive effect of agricultural subsidies played a leading role in reducing pollution by 15.4029 million tons. Perhaps the tax-free policy promoted agricultural mechanization and technology, similar to the inhibitory effect of emission intensity. The results also show that the expansion of government expenditures will aggravate the loads of ANSP emissions (i.e., expansionary fiscal policy leads to a deterioration of environmental quality) (Ullah, Majeed, and Chishti, 2020).

Different types of agricultural subsidies have different effects on nonpoint source pollution. Agricultural output subsidies, including grain subsidies and chemical fertilizer input subsidies, will stimulate farmers to use less fertile, degraded land for cultivation, which leads to the destruction of ecological balance. As grain and input subsidies accounted for the majority of agricultural subsidies in the 2000s (Huang, Wang, and Rozelle, 2013), this problem was prominent in 2004 when the three-part agricultural subsidies policy was first proposed. The intensive factor caused an increase of 1.4289 million tons of ANSP emissions at that time because farmers relied on limited cultivated land resources for extensive production. In the same year, the strengthening of fiscal support for agriculture reduced ANSP emissions by 3.8193 million tons. On the other hand, China's Ministry of Agriculture was implementing the reform of the agricultural subsidy system based on green and ecological agriculture to alleviate the "quantity safety of food and quality of environment" dilemma in agriculture. Moreover, subsidies for the use of pollution-reducing agricultural inputs and pollution remediation activities could effectively improve the agricultural environment (Abler, 2015). In addition, when total agricultural support grew by 29.02% from US$186,426.6 million to US$240,526.6 million, the subsidy incentive effect became stronger again from 2014 to 2015, decreasing ANSP by 4.3535 million tons. However, according to Yi, Sun, and Zhou (2015), most farmers have small plots of cultivated land, so only a few of them can apply for machinery subsidies, which accounted for less than 10% of the four agricultural subsidies (Huang, Yan, and Huang, 2020). Hence, it is appropriate for the government to adopt agricultural subsidies, especially abatement innovation subsidies and pollution remediation subsidies to get rid of the dilemma of agricultural yield growth and environmental pollution.

Conclusions and Policy Implications

The issue of agricultural nonpoint source pollution (ANSP) has attracted increasing attention, but the driving forces of the changes in ANSP emissions, which form the basis for emission reduction, have been ignored. We apply the LMDI method to decompose changes in China's ANSP into five factors: emission intensity, scale of agricultural production, labor intensification effect, urbanization, and population scale to explore the contributions of these factors in different regions from 2000 to 2018. Our research then examines the driving forces in the context of agricultural policies and discusses the incentive effects of agricultural subsidies on changes in ANSP emissions. Our main conclusions are as follows:

(i) Among agricultural production activities, livestock and poultry breeding have produced the highest levels of pollution; regionally, the southeast coast and northeast China have maintained low pollution, while the western region has higher pollution levels.
(ii) Intensity and urbanization inhibit ANSP loads. Emission intensity especially played a major restraining role in most years, while agricultural production scale, labor intensification, and population enhance emissions, and the scale factor has the strongest role in increasing pollution.
(iii) Changes in ANSP emissions are correlated with different agricultural policies. At the early stage, the expansion of production scale required by agricultural economic development led to an increase in ANSP emissions, particularly in the eastern region. The intensity effect played a dominant role in decreasing pollution in the stage of agricultural tax reform and the period of controlling prominent agricultural pollution.
(iv) The incentive effect of subsidies significantly reduces ANSP emissions, while financial expenditures will increase pollution. Different types of agricultural subsidies have different impacts on ANSP emissions.

To construct an effective path to achieve China's sustainable agricultural development, we suggest four policies:

(i) Use "recycling agriculture" to guide the development of environmentally friendly agriculture. Continuously improve the utilization efficiency of agrochemicals, reduce the intensity of chemical fertilizers application, increase the resource utilization of livestock manure waste, and accelerate the transformation from traditional patterns of husbandry to the scale development pattern.
(ii) Adopt appropriate pollution reduction targets and policies in light of local conditions. Each province should make focused regional plans for the control of ANSP emissions based on local stages of agricultural economic development. The western region especially should pay more attention to the increasing trend of pollution.
(iii) Vigorously promote green production technologies in agriculture. Emission intensity is the major restraining factor, and technological progress is an effective way to improve efficiency and reduce emission intensity. Investments in agricultural science and technology innovation

should increase, and development of agricultural mechanization and informatization should be promoted. Meanwhile, continuing to encourage urbanization will enhance the carrying capacity of cities.

(iv) The role of the economic incentive mechanism in ANSP management ought to be taken more seriously. Comprehensive application of multiple policy tools and improvements in the level of agricultural machinery, innovation, and green subsidies will help mitigate ANSP emissions.

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Appendix A: Decomposition Formula of ANSP Emissions from the Agricultural Policies Perspective

The mathematical identity of driving forces decomposition:

$$NSP = \sum_{i}^{n} \frac{NSP_i}{Ae_i} \times \frac{Ae_i}{Te_i} \times \frac{Te_i}{Gdp_i} \times \frac{Gdp_i}{Pop_i} \times Pop_i = \sum_{i}^{n} Si_i \times Fsa_i \times Sfe_i \times Pgdp_i \times Pop_i, \tag{A1}$$

where Ae_i is agricultural finance expenditure, which is expressed as the expenditure of local finance on agriculture, forestry, and water affairs; and Te_i is total fiscal expenditure, which is expressed by the local finance general budget expenditure. Nonpoint source pollution (*NSP*) was decomposed into five factors:

- the incentive effect of agricultural subsidies ($Si_i = \frac{NSP_i}{Ae_i}$),
- fiscal support for agriculture ($Fsa_i = \frac{Ae_i}{Te_i}$),
- scale of fiscal expenditure ($Sfe_i = \frac{Te_i}{Gdp_i}$),
- the level of economic development ($Pgdp_i = \frac{Gdp_i}{Pop_i}$), and
- population scale.

The data are from the *China Statistical Yearbook* and the *China Financial Statistics Yearbook*. The additive decomposition formula is as follows:

$$NSP^T - NSP^0 = \Delta NSP_{Tot} = \Delta NSP_{Si} + \Delta NSP_{Fsa} + \Delta NSP_{Sfe} + \Delta NSP_{Pgdp} + \Delta NSP_{Pop}; \tag{A2}$$

$$\Delta NSP_{Si} = \sum_{i}^{n} \frac{NSP_i^T - NSP_i^0}{\ln NSP_i^T - \ln NSP_i^0} \ln\left(\frac{Si_i^T}{Si_i^0}\right); \tag{A3}$$

$$\Delta NSP_{Fsa} = \sum_{i}^{n} \frac{NSP_i^T - NSP_i^0}{\ln NSP_i^T - \ln NSP_i^0} \ln\left(\frac{Fsa_i^T}{Fsa_i^0}\right); \tag{A4}$$

$$\Delta NSP_{Sfe} = \sum_{i}^{n} \frac{NSP_i^T - NSP_i^0}{\ln NSP_i^T - \ln NSP_i^0} \ln\left(\frac{Sfe_i^T}{Sfe_i^0}\right); \tag{A5}$$

$$\Delta NSP_{Pgdp} = \sum_{i}^{n} \frac{NSP_i^T - NSP_i^0}{\ln NSP_i^T - \ln NSP_i^0} \ln\left(\frac{Pgdp_i^T}{Pgdp_i^0}\right); \tag{A6}$$

$$\Delta NSP_{Pop} = \sum_{i}^{n} \frac{NSP_i^T - NSP_i^0}{\ln NSP_i^T - \ln NSP_i^0} \ln\left(\frac{Pop_i^T}{Pop_i^0}\right). \tag{A7}$$

Table A1. Annual Decomposition Results of China's ANSP Emissions Based on Agricultural Policies

	Changes in ANSP Emissions (10^4 tons)					
Time Interval	ΔNSP_{Si}	ΔNSP_{Fsa}	ΔNSP_{Sfe}	ΔNSP_{Pgdp}	ΔNSP_{Pop}	ΔNSP_{Tot}
2000–2001	−376.01	−120.59	318.73	181.17	10.31	13.61
2001–2002	−351.99	73.42	139.83	203.42	12.76	77.44
2002–2003	−31.70	−243.28	−30.06	228.24	14.16	−62.65
2003–2004	−940.99	743.52	126.96	269.59	12.98	212.06
2004–2005	−16.35	−381.93	194.27	313.10	−11.50	97.60
2005–2006	−418.65	−86.37	214.32	295.87	14.65	19.82
2006–2007	−1540.29	531.71	236.69	292.82	11.60	−467.47
2007–2008	−645.58	115.02	313.45	227.68	13.05	23.62
2008–2009	−823.89	386.08	244.81	226.14	12.57	45.71
2009–2010	−384.85	−22.88	156.54	259.88	7.30	15.99
2010–2011	−472.66	−25.12	236.46	244.14	8.93	−8.26
2011–2012	−349.45	65.22	104.47	214.43	10.90	45.57
2012–2013	−213.37	−1.60	31.12	192.57	10.88	19.59
2013–2014	−121.26	−11.72	−15.01	167.25	11.63	30.89
2014–2015	−435.35	143.69	119.04	153.71	14.68	−4.23
2015–2016	−187.42	20.36	−18.75	142.67	14.00	−29.14
2016–2017	−138.30	−104.72	13.50	133.64	13.27	−82.61
2017–2018	−275.14	70.20	33.83	126.30	11.91	−32.90