

Article

Structural Change and Its Impact on the Energy Intensity of Agricultural Sector in China

Hongyun Han ¹ and Shu Wu ^{1,2,*} 

¹ Center for Agricultural and Rural Development, School of Public Affairs, Zhejiang University, Hangzhou 310058, China; hongyunhan@zju.edu.cn

² School of Management, Zhejiang University, Hangzhou 310058, China

* Correspondence: wushu@zju.edu.cn; Tel.: +86-152-6703-0943

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Abstract: China's agricultural structure has undergone significant changes for the past four decades, mainly presenting as the fall of sown proportion of grain crops and the rise of vegetables, as has its energy consumption. Employing the panel data on 30 provinces during 1991–2016, this paper empirically explores the impact of agricultural structure changes (ASC) on the energy intensity of agricultural production (EIAP), direct energy intensity of agricultural production (DEIAP) and indirect energy intensity of agricultural production (IEIAP) in China. Besides, the regional heterogeneity of such impact is examined. The results show that: (1) ASC increases EIAP and IEIAP significantly, while ASC decreases DEIAP, which is explained by the structural effect and different planting modes of different crops; (2) the impact in the three administrative regions is similar to national situation, except the impact of ASC on DEIAP in the West Region, which is explained by regional differences of vegetable mechanization; (3) the result of the six vegetable production regions reveals greater regional heterogeneity, and this is attributed to the scale economy effect and the incremental effect of vegetable mechanization; and (4) fuel price, income, agricultural labor, old dependency ratio, and fiscal expenditure have different but significant impacts on EIAP, DEIAP, and IEIAP. Finally, some policy implications are given.

Keywords: agricultural structure changes; energy intensity; regional heterogeneity; mechanization; chemical fertilizers

1. Introduction

Remarkable agricultural growth has been achieved in China since 1978. The real gross value of agricultural output grew from 111.76 billion China Yuan (CNY) to 636.09 billion CNY for the years of 1978–2016, with an average growth rate of 4.68% per year. Such growth derives not only from institutional reforms [1–3] and technical progress [4–6], but to a large extent, from rising agricultural inputs like chemical fertilizers and pesticides [7–9], machinery [10,11], and energy [12–14]. During 1991–2016, China's total power of agricultural machinery soared from 282.54 million kilowatts to 1104.99 million kilowatts; meanwhile, its consumption of nitrogen fertilizer, phosphate fertilizer, potash fertilizer, compound fertilizer, and pesticides rose from 17.26 million tons, 5 million tons, 1.74 million tons, 4.06 million tons, and 0.76 million tons to 23.11 million tons, 8.30 million tons, 6.37 million tons, 22.07 million tons, and 1.74 million tons, respectively. The growth of these inputs drove energy consumption of agricultural production (ECAP) increase from 66.65 million tons of standard coal equivalent (Mtce) to 98.05 Mtce over this time span, because energy is used directly as fuels for agricultural machinery and indirectly as raw materials for chemical fertilizers and pesticides [15]. As a result, nearly one-quarter of global ECAP comes from the Chinese agricultural sector [9].

However, China's astonishing agricultural development has come with a price [16]. The growing ECAP is accompanied by non-point source water pollution [17], soil pollution [18], air pollution [19], as well as extensive greenhouse gas (GHG) emissions [20]. According to China's Bulletin on the First National Census on Pollution Sources, agriculture has replaced industry as the major source of water pollution since 2005, including nitrogen (57.19%), phosphate (67.27%), and chemical oxygen demand (43.71%) [21]. In addition, China's Initial National Communication on Climate Change showed that agriculture-related GHG emissions are calculated to occupy nearly 17% of its total emissions [22]. The situation relating to GHG emissions and air pollution gets worse due to upstream activities relating to fertilizer production and transportation, midstream activities associated with fertilizer utilization, and agricultural structural changes [19,23,24], and in 2007, the proportion increased to about one-third [25]. Correspondingly, agriculture-related CO₂ emission grew from 116.26 million tons in 2001 to 185.66 million tons in 2012 [26]. Over-exploitation of resources and severe environmental pollution has hampered the sustainable development of China's agricultural sector.

Chinese government has proposed to realize agricultural modernization by 2035, which is characterized by mechanization and extensive use of chemical fertilizers [27]. The 13th Five-Year Plan for the Development of Agricultural Mechanization has set the goals of increasing the comprehensive mechanization rate of crops' tillage and harvest from 63% to 70%, improving the comprehensive mechanization rate of tillage and harvest for wheat, rice, and corn to above 80%, and increasing the total power of agricultural machinery to 1.2 billion kilowatts during 2015–2020. It is inevitable that more machinery and chemical fertilizers will be adopted in China's agricultural modernization process, thereby improving ECAP and causing associated environmental problems. Facing a dilemma of sustaining agricultural development and tackling agriculture-rooted environmental issues, a common consensus of promoting agricultural energy efficiency has been reached [14].

As the most energy-intensive country in the world, China has put energy conservation and efficiency improvement on its agenda for years [28]. The latest is the 13th Five-Year Plan for Energy Development, which aims to reduce energy intensity by 15% in 2020 compared to the 2015 level. Meanwhile, agriculture is expected to play a key role in reducing GHG emissions [12]. Contrary to the growing ECAP, EIAP in China reveals a declining trend. For the years of 1991–2016, EIAP decreased from 1.31 tons of standard coal equivalent (tce)/10,000 CNY to 0.46 tce/10,000 CNY. Correspondingly, IEIAP and DEIAP exhibited similar fluctuation trends, and declined from 0.85 tce/10,000 CNY and 0.46 tce/10,000 CNY to 0.30 tce/10,000 CNY and 0.17 tce/10,000 CNY, respectively. To achieve sustainable agricultural modernization, it is important to figure out determinants driving the decline of EIAP, IEIAP, and DEIAP in China.

Since 1978, the main problem of China's agriculture has shifted from insufficient supply to structural disequilibrium [29]. As a direct response to changing market demand, regional comparative advantages, and government policies, China's agricultural structure has changed significantly [9,29]. The sown proportion of grain crops decreased from 78.05% in 1991 to 69.38% in 2016, while that of vegetable increased from 4.55% to 13.70%. Structural change and its impact on the energy intensity of China's agricultural sector deserve special attention because different crops vary significantly in both the type and amount of energy-related agricultural inputs, which result in significant changes of agricultural energy intensity [30–32]. Besides, China's agricultural sector must undergo a significant transformation of higher energy efficiency for food production and transportation in order to meet the challenges of food security and climate change [33]. Due to its insignificant proportion of about 6% of total energy consumption, agricultural energy in China has not received enough attention [12,34], let alone the impact of ASC on EIAP, DEIAP, and IEIAP. The existing research on agricultural energy in China mainly focuses on an energy conversion coefficient or efficiency [13,35–38], impact of energy on agricultural output [39], current consumption situation and demand forecasting [14,40,41], affecting factors [34,42,43], and environmental effect [12,44–46].

This study attempts to investigate the impact of ASC on EIAP, DEIAP, and IEIAP in China, and regional heterogeneity of such an impact in terms of the administrative division of regions and the six

vegetable production regions, which will shed light on the sustainable growth of China's agricultural sector. This study makes three central contributions. Firstly, to the writers' knowledge, this study originally estimates the impact of ASC on EIAP, DEIAP, and IEIAP in China. Secondly, while existing literature only focuses on DEIAP and treat DEIAP as the gross EIAP in China, both DEIAP and IEIAP are taken into consideration in this study because the latter is the major form of EIAP in China and has been excluded from official statistics and ignored by the existing literature. Thirdly, a rich dataset at a provincial level is used, which allows us to take the high level of regional heterogeneity into consideration.

The remainder of this paper is organized as follows: Section 2 reviews the evolution of ASC and EIAP in China and relevant literature; Section 3 presents the methodology and data used; Section 4 shows the empirical results and its corresponding discussion; and Section 5 ends the research with some conclusions and policy implications.

2. ASC and EIAP in China: Evolution and Literature Review

2.1. The Evolution of ASC and EIAP in China

Economic development is often accompanied by systematic changes of economic structure [47], and agricultural planting structure refers to the composition of different crops and their corresponding proportion to the total sown area. In this study, agriculture in its narrow sense is adopted and refers to the cultivation of farm crops [48]. Influenced by market demand for more commercial crops, regional comparative advantages and government policies, remarkable ASC have been witnessed in China and there are four stages of policy adjustment on agricultural structure since 1990 [9,29,49,50].

Before the 1990s, China's monotonous agricultural structure, rooted in "Taking Grain as the Key Link" policy, led to the dull sale for grain and cotton, and the shortage of commercial agricultural products. The agricultural market reform motivated the production of commercial agricultural products, which, however, were difficult to sell in the early 1990s. Hence, there came the first stage of policy adjustment (1991–1997), whose goal was to develop high-yield, high-quality, and high-efficiency agriculture. During 1997–1998, agricultural product prices fell across the board and farmers' income stagnated. There came the second stage of policy adjustment to boost agricultural development (1998–2003).

After joining the World Trade Organization, Chinese agriculture faced tremendous challenges from global agriculture. In 2004, Opinions on Some Policies for Promoting Farmers' Income was issued and improving the overall quality of agriculture and rural economy and raising the international competitiveness of agricultural products became the focus of policy adjustment on agricultural structure during 2004–2014. In 2015, the Ministry of Agriculture (MOA) started a new round of spontaneous adjustment of agricultural structure (post 2015), which can be summarized as "Two Stabilization, Two Increase and Two Enhancement". Under the background that the sown proportion of other crops kept basically unchanged, the sown proportion of grain crops decreased from 78.05% in 1991 to 69.38% in 2016, while that of vegetable increased from 4.55% to 13.70% (see Figure 1). Simultaneously, the sown area of grain crops and vegetable increased from 112.31 million hectares and 6.55 million hectares to 113.03 million hectares and 22.33 million hectares, respectively.

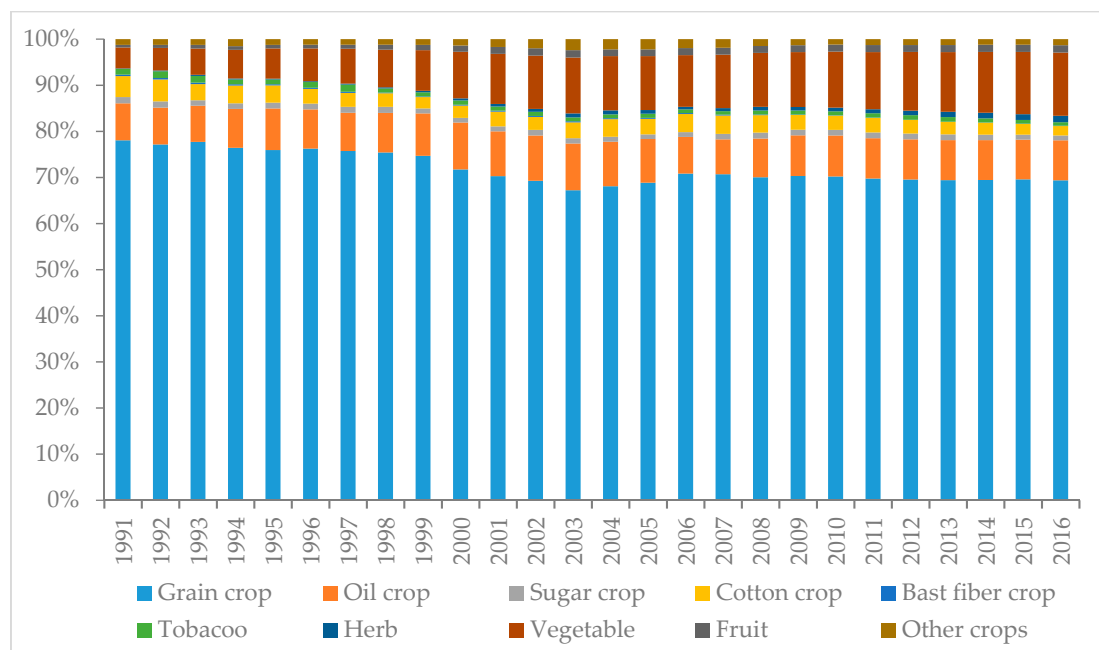


Figure 1. The structural change of agricultural sector in China and energy consumption during 1991–2016. (Data source: [51]).

In the provincial level, the decreasing amplitudes of the sown proportion of grain crops in Fujian (−27.06%), Zhejiang (−25.17%), Guangxi (−24.43%), Qinghai (−23.92%), Hainan (−23.10%), and Beijing (−22.47%) were lower than −20.00%, and the increasing amplitudes of the sown proportion of vegetable in Shanghai (28.77%), Hainan (28.17%), Fujian (23.79%), Zhejiang (22.50%), and Beijing (20.03%) were higher than 20.00% (see Figure 2a,b). Those changes result in significant changes of EIAP, DEIAP, and IEIAP because different crops vary significantly in both the type and volume of agricultural inputs [32]. For instance, the indirect energy consumed per hectare for rice is 224.67 kilograms of standard coal equivalent (kgce) in 2016, while that for potato is 416.58 kgce.

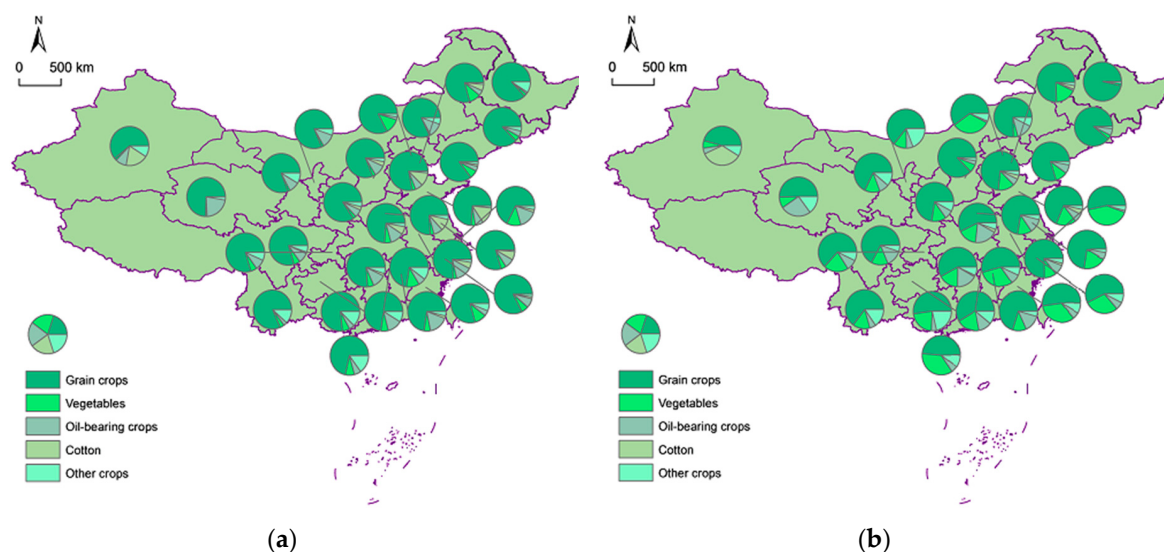


Figure 2. Sown structure of China's agricultural sector in 1991 and 2016: (a) Sown structure of China's agricultural sector in 1991; (b) Sown structure of China's agricultural sector in 2016. (Data source: [51]).

Energy intensity refers to the ratio of energy consumption to economic output, which assesses the energy efficiency of a country or a region. The lower the energy intensity, the higher the energy

efficiency. During 1991–2016, ECAP increased from 66.65 Mtce to 98.05 Mtce. Among the ECAP, direct energy consumption of agricultural production (DECAP) rose from 23.24 Mtce to 35.47 Mtce, and indirect energy consumption of agricultural production (IECAP) grew from 43.41 Mtce to 62.58 Mtce. Compared to the growing ECAP, DECAP, and IECAP, EIAP in China reveals an opposite trend. For the years of 1991–2016, EIAP firstly decreased from 1.31 tce/10,000 CNY to 0.94 tce/10,000 CNY in 1996, maintained invariable by 2003, and continued to decrease to 0.46 tce/10,000 CNY. Correspondingly, IEIAP and DEIAP exhibited similar fluctuation trends, and declined from 0.85 tce/10,000 CNY and 0.46 tce/10,000 CNY to 0.30 tce/10,000 CNY and 0.17 tce/10,000 CNY, respectively (see Figure 3).

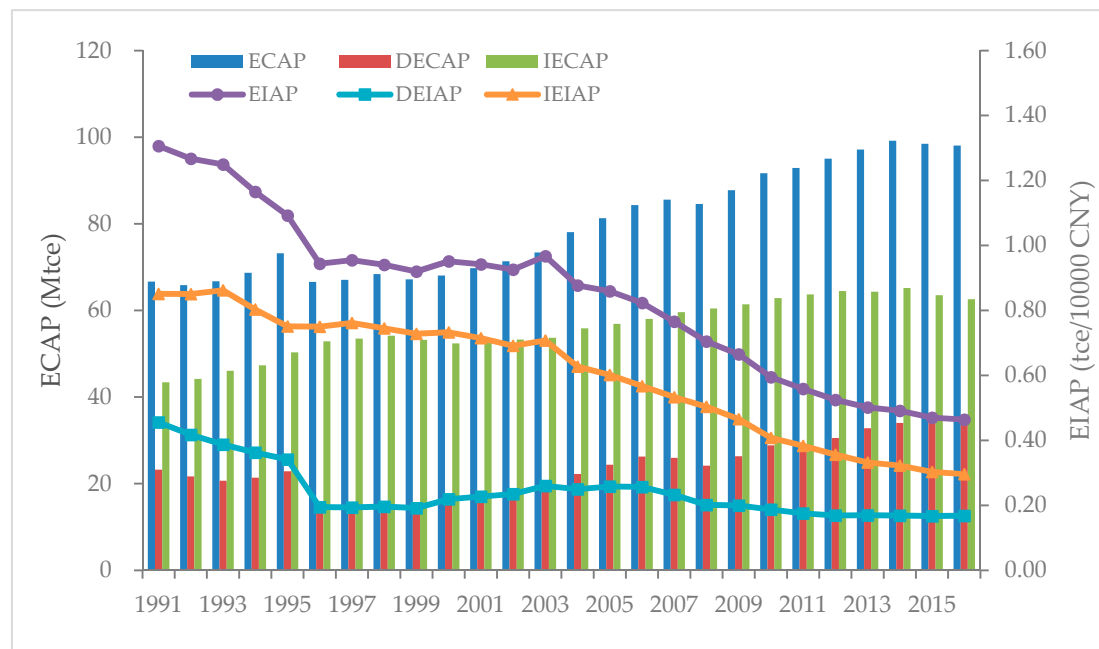


Figure 3. ECAP, DECAP, IECAP, EIAP, DEIAP, and IEIAP in China. Data source: [52].

As a result of China's vast territory, energy intensity exhibits huge regional heterogeneity [53], and so does EIAP, DEIAP, and IEIAP (see Figure 4). In 1991, the EIAP, DEIAP, and IEIAP of Central Region was higher than those of East Region and West Region (see Figure 4a,c,e). However, the situation changed and in 2016, the EIAP, DEIAP, and IEIAP of West Region was higher than those of Central Region and East Region (see Figure 4b,d,f). Specifically, in 1991, the EIAP of Shanxi was 3.55 tce/10,000 CNY, around 4.67 times that of Guangdong at 0.76 tce/10,000 CNY, and in 2016, the EIAP of Jilin was 1.04 tce/10,000 CNY, about 4.33 times that of Tianjin at 0.24 tce/10,000 CNY. Comparing Figures in 1991 with Figures in 2016, it can be seen that, in line with EIAP, DEIAP, and IEIAP of the national level, EIAP, DEIAP, and IEIAP, of the regional level exhibit a generally declining trend during 1991–2016, except for several provinces. To achieve the goal of agricultural modernization, it is necessary to discern the influential factors leading to the decline of EIAP, DEIAP, and IEIAP in the past decades to further decrease EIAP in China.

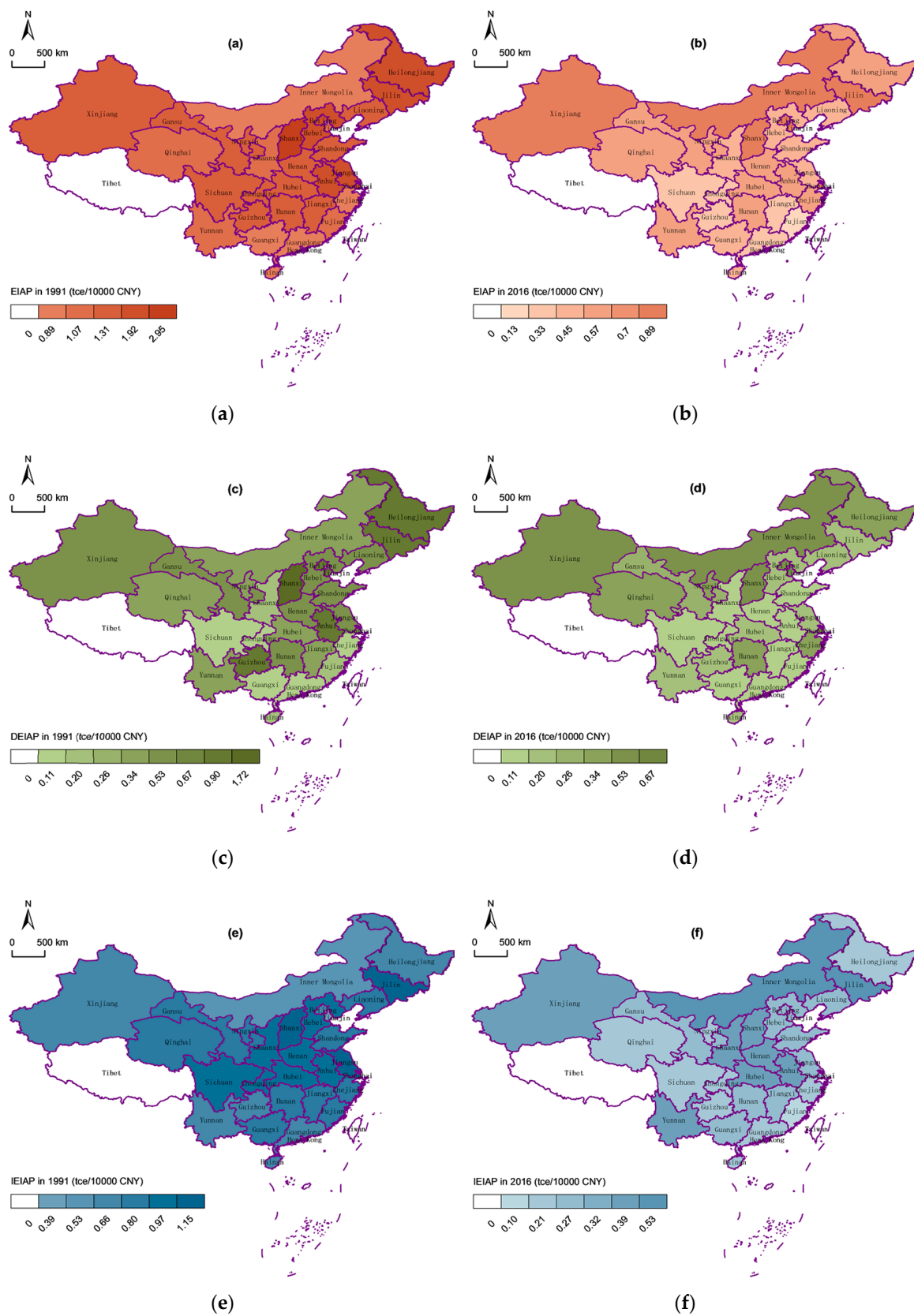


Figure 4. (a) EIAP in 1991; (b) EIAP in 2016; (c) DEIAP in 1991; (d) DEIAP in 2016; (e) IEIAP in 1991; and (f) IEIAP in 2016. Data source: [52].

2.2. The Relationship between ASC and EIAP: A Literature Review

Economic structural changes have been proved as an important factor influencing energy intensity [54–64]. The share of added value of secondary sector or tertiary sector in GDP is often adopted as the indicator of economic structural changes. In terms of research methods, there are two lines of literature on energy intensity and economic structural changes.

The first line of literature attributes the change in energy intensity to some pre-defined effects using decomposition analysis. Index decomposition analysis (IDA) and structure decomposition analysis (SDA) are two popular techniques [65]. IDA uses aggregate sector information and decomposes the change of energy intensity into the energy intensity effect and industrial structure effect [66–70]. In recent studies, energy structure effect has been introduced as another effect [28,65]. Under the framework of IDA, most studies, however, fail to explain what facilitating the change of those components [65]. However, there are some exceptional examples [28,65,71,72].

Compared to IDA, SDA had been more commonly used to decompose quantity indicators like gross energy consumption, rather than intensity indicators like energy intensity. However, the situation has changed due to the wide use of intensity indicators to assess economic performance and set economic goals since 2010 [73]. Generally, SDA decomposes energy intensity into production effect, structure effect, Leontief effect, intensity effect, and final demand effect [74]. While some use additive decomposition analysis [75–78], others use multiplicative decomposition analysis [79–84].

However, those decomposition techniques lack “any casual relationships by nature of the identity relation” and “fail to offer any explanations as to why a given component, for example, structural effect, is the dominant factor in explaining actual energy consumption changes” [85]. More commonly, another line of literature treats the economic structural changes as a determinant of energy intensity through regression analysis. Compared to the decomposition analysis, plenty of the methods are applied in those studies, including fixed effect model, dynamic panel data model, nonlinear threshold co-integration model, Spatial Durbin error model, data envelopment analysis, and so on. While some use the share of added value of tertiary sector to GDP as the structure indicator [86–88], the majority adopts the share of added value of secondary sector [53–64,89,90]. This is because the secondary sector consumes the majority of energy in most countries and is more energy-intensive than other industries.

According to those studies, economic structural changes affect energy intensity through two effects. The first is called the structural effect. Compared to primary industry or tertiary industry, secondary industry is more energy-intensive. Hence, if the share of secondary industry grows, the overall energy intensity grows [91]. The second is the income effect. The improvement of income through industrialization often stimulates market demand for more goods, such as automobiles, air-conditioners, and refrigerators, which enhances energy intensity as well [92]. As can be seen, the current literature remains in the level of primary industry, secondary industry and tertiary industry. To the best of the authors’ knowledge, few empirical studies investigate how the internal structure of an industry influences its energy intensity, let alone the influence of ASC on EIAP, IEIAP, and DEIAP in China.

Besides, a massive amount of literature focuses on the determinants of the declining energy intensity. The majority, however, stay in aggregate energy intensity, and few pay attention to the drivers of its declining EIAP, IEIAP, and DEIAP. Only few studies are concerned with quantity indicators like ECAP [43] and energy consumption of primary industry (ECPI) [14,34,42], and some of them focus on efficiency indicators like energy efficiency of primary industry (EEPI, inverse of energy intensity) [93] and total factor energy efficiency of primary industry (TFEEPI) [94,95]. Benefiting from the same research object and proxy variables, those studies shed light on the determinants of EIAP, IEIAP, and DEIAP in China (see Table 1).

Table 1. Studies on the determinants of energy consumption of agriculture/primary industry in China.

Authors	Period	Method	Dependent Variable	Determinants
Fei and Lin, 2017. [14]	1980–2012	Co-integration analysis, vector error correction model, scenario analysis	ECPI	1–5
Li and Jing, 2011. [22]	1978–2009	Linear regression model	EIPI	1, 2, 33, 34
Xing et al., 2014. [34]	1988, 1990, 1995, 2000, 2005, 2010	Spatial regression model	ECPI	1, 3, 13, 25
Peng and An, 2012. [42]	2000–2008	Fixed-effect model	ECPI	1, 3, 6, 13, 25, 26
Xing et al., 2015. [43]	1998–2013	Panel data model	ECAP	21–24
Guo et al., 2012. [93]	1997–2008	Fixed-effect model	EEPI	8, 11, 27–32
Zhou et al., 2016. [94]	2003–2012	DEA method, Tobit model	TFEPI	8, 9, 11–20
Ran and Zhou, 2017. [95]	2000–2013	SBM-TOBIT model	TFEPI	2, 6–10

Notes: 1. Added value of primary industry; 2. Proportion of agricultural added value to added value of primary industry; 3. Machinery power of primary industry; 4. Fiscal expenditure on primary industry; 5. Retail price index of power and fuel; 6. Purchasing price index of raw material, fuel and power; 7. Proportion of technicians to labor force in primary industry; 8. Rural per capita income; 9. Ratio of added value of primary industry to GDP; 10. Fixed capital stock per capita in primary industry; 11. Proportion of primary industry's fiscal expenditure to total fiscal expenditure; 12. Capital stock of primary industry; 13. Labor force of primary industry; 14. Rural per capita expenditure; 15. Electricity consumption per mu; 16. Proportion of effective irrigation area; 17. Ratio of foreign investment to GDP; 18. Per capita GDP; 19. Ratio of R & D expenditure to added value of primary industry; 20. Proportion of rural labor force with education level of senior high school or above; 21. agricultural added value; 22. Labor force of agriculture; 23. Investment in agricultural fixed asset; 24. Lagged term of ECAP; 25. Investment in fixed asset of primary industry; 26. Lagged term of energy consumption of primary industry; 27. Agricultural mechanization level; 28. Power of agricultural machinery per hectare; 29. Added value of primary industry per labor; 30. Ratio of rural labor working for secondary and tertiary industry to total rural labor force; 31. Number of agricultural professional technicians in state-owned enterprises and institutions; 32. Education level of rural labor force; 33. Proportion of grain crops' sown area to commercial crops' sown area; and 34. Proportion of non-agricultural investment to agricultural investment. Data source: Authors' own summarization.

3. Methods and Materials

3.1. Econometric Model

Panel data models have been widely adopted to investigate the impact of economic structural changes on energy intensity [53,59,61,86,88,92,96]. To empirically examine the impact of ASC on EIAP, DEIAP, and IDIAP in China, a panel data regression is employed in this study as well. Compared to conventional cross-sectional data models and time-series data models, panel data models possess several major advantages, including decreasing multi-collinearity among explanatory variables, controlling the impact of omitted variables, allowing for heterogeneity between individuals, providing a more accurate inference of model parameters and uncovering dynamic relationships [97]. Hence, a panel data model, as follows, is adopted.

$$EI_{it} = \beta_0 + \beta_1 Structure_{it} + \beta_2 X_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (1)$$

where EI_{it} is the proxy of $EIAP_{it}$, $DEIAP_{it}$, and $IEIAP_{it}$. $EIAP_{it}$ is the energy intensity of agricultural production for province i in year t . $DEIAP_{it}$ and $IEIAP_{it}$ are the direct energy intensity and indirect energy intensity of agricultural production for province i in year t , respectively. While $DEIAP_{it}$ relates to production activities within farms, such as fuels for power machinery and electricity for processing machinery, $IEIAP_{it}$ is associated with energy used as raw materials for the production of agricultural inputs, such as chemical fertilizers and pesticides [15]. $Structure_{it}$ refers to the agricultural structure for province i in year t . X_{it} is a set of covariates, including energy price, per capita income, agricultural labor force, old dependency ratio, governmental fiscal expenditure on agriculture, and agricultural mechanization. β_0 is the constant; β_1 and β_2 are parameters to be estimated; λ_t is the year-specific

effect and μ_i is the province-specific effect; ε_{it} is an error term with $E(\varepsilon_{it}) = 0$ for all i and t , capturing all other omitted factors.

$$EI_{it} = \beta_0 + \beta_2 X_{it} + \beta_3 \text{Structure}_{it} * \text{East}_t + \beta_4 \text{Structure}_{it} * \text{Middle}_t + \beta_5 \text{Structure}_{it} * \text{West}_t + \lambda_t + \mu_i + \varepsilon_{it} \quad (2)$$

$$EI_{it} = \beta_0 + \beta_2 X_{it} + \beta_6 \text{Structure}_{it} * \text{SSR}_t + \beta_7 \text{Structure}_{it} * \text{YRB}_t + \beta_8 \text{Structure}_{it} * \text{LP}_t + \beta_9 \text{Structure}_{it} * \text{YGP}_t + \beta_{10} \text{Structure}_{it} * \text{NHR}_t + \beta_{11} \text{Structure}_{it} * \text{HCP}_t + \lambda_t + \mu_i + \varepsilon_{it} \quad (3)$$

This paper uses data from 30 regions of China to capture the regional dimension. Specifically, to verify the existence of regional heterogeneity, we employ two categories of regional groupings—the administrative division of regions and the six vegetable production regions. The latter captures some of the spatial heterogeneity, as well as the discrepancies between national and regional ASC on EIAP, DEIAP, and IEIAP, in greater detail than the administrative division of regions. From the perspective of the administrative division of regions, China is divided into East Region, Central Region, and West Region (see Figure 5a) [98]. From the perspective of the six vegetable production regions, China is divided into South and Southwest Region (SSR), Yangtze River Basin (YRB), Loess Plateau (LP), Yunnan-Guizhou Plateau (YGP), Northern High-Latitude Region (NHR), and Huang-Huai-Hai and Circum-Bohai-Sea Plain (HCP) (see Figure 5b) [99]. Three dummy variables for the three administrative regions, East_t , Middle_t , and West_t , as well as six dummy variables for the six vegetable production regions, SSR_t , YRB_t , LP_t , YGP_t , NHR_t , and HCP_t , are added to investigate whether there are significant differences between regions. In a second stage, an interaction effect between each region and agricultural structure is created to account for the differential effect of ASC in each region. β_3 – β_{11} are parameters to be estimated.

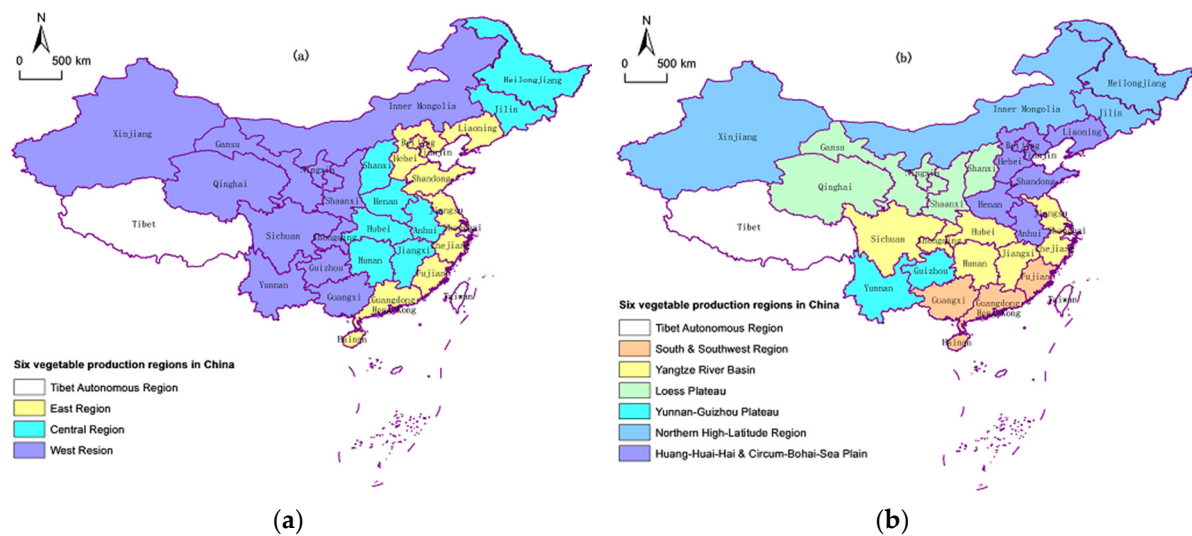


Figure 5. (a) The administrative division of China; and (b) the six vegetable production regions in China. Data source: [98,99]

3.2. Data and Descriptive Statistics

The paper uses data of 30 provinces, autonomous regions and directed-controlled municipalities in mainland China for 1991–2016 to capture the spatial or regional dimension, excluding the Tibet Autonomous Region due to severe data missing (see Figure 5). EIAP is measured by ECAP divided by agricultural added value; DEIAP is measured by DECAP divided by agricultural added value; IEIAP is measured by IECAP divided by agricultural added value; Structure is measured by vegetable sown area divided by total sown area. Inspired by studies listed in Table 1 and some literature

on aggregate energy intensity in China, energy price, per capita income, agricultural labor force, old dependency ratio, fiscal expenditure on agriculture, and agricultural mechanization are selected as controlled variables.

Due to data availability, this paper follows the studies [100,101], and employs rural retail price index of fuels as an approximation for energy price. The price elasticity of energy demand is generally negative, which has been proved appropriate in explaining China's aggregate energy intensity [59,67,92]. However, the normal function of price mechanism bases on complete marketization, while China's energy system is not fully market-oriented, and the long-term energy-price regulation has resulted in energy-price distortion [102]. For instance, the results of [100,101] have shown that the price mechanism functions poorly in China's rural residential energy transition. Hence, the effect of energy price on EIAP in China depends on the game between market power and government power.

Income is measured by agricultural added value divided by agricultural labor force. Compared to other indicators, the influence of income on energy intensity is more complicated. Firstly, economic development is usually accompanied by income growth, while rising income often diversifies energy demands as well as increases energy intensity [67,71]. For instance, with a higher income level, more farmers can afford some simple agricultural machinery, which increases EIAP. Besides, income level is actually a proxy of socioeconomic development. With the improvement of income, people's attitude towards environment and natural resources will be enhanced. The examples are not limited to the adoption of more energy-efficiency technology and environmentally friendly behaviors [72].

Labor is measured by total agricultural labor force input divided by the total sown area. Theoretically, agricultural labor force affects EIAP through two effects. Firstly, farmers' households are still the basic units of agricultural production in China, which impedes the mass adoption of agricultural machinery to some degree. As a substitute of agricultural machinery, increasing the agricultural labor force contributes to the decline of EIAP [34,43]. Secondly, agricultural labor force is actually a reflection of agricultural production scale. More labor force input often implies a larger agricultural production scale, while the improvement of agricultural production scale increases EIAP [42]. Similar to the effect of energy price, the effect of labor force on EIAP in China is actually a comprehensive result of the two effects.

Dependency refers to old dependency ratio and is measured by rural population aged over 65 divided by rural population aged 15–64. The aging population has become a prevalent social issue globally and its impact on agricultural production is unprecedented [103]. With 106 million agricultural workers aged 55 and above, accounting for 34% of its total agricultural workers, China is suffering from an aging agricultural population. It has been proved that the increasing old dependency ratio in China will improve energy consumption and the impact is growing [104].

Machinery refers to machinery power and is measured by total agricultural machinery power divided by the total sown area. The popularization of agricultural machinery has significantly improved agricultural productivity in China, which is the main consumer of DECAP. According to the classification standards of the agricultural industry, agricultural machinery includes tractors, planting machinery, farm and sideline products primary processing machinery, animal husbandry machinery, fishery machinery, timber and fruit machinery, farmland and capital construction machinery, and farm transport vehicles [105]. Generally, the higher the agricultural mechanization level, the higher the EIAP. In addition, the increasing mechanization level is often accompanied by the rising energy efficiency, which leads to the decline of energy intensity.

Fiscal expenditure refers to government's fiscal expenditure on agriculture. Evidence from both developed and developing countries has shown that fiscal expenditure from government significantly affects the performance of the agricultural sector [106,107]. Since the reform of government revenue and expenditure in 2007, Chinese government's expenditure on agriculture, forestry and water affairs increased to 1738.05 billion CNY by 2015, with an average growth rate of 22% per year. Of the expenditure, a large proportion is invested in agricultural fixed assets, which are used for enlarging agricultural production scale, purchasing or upgrading agricultural machinery and equipment,

improving infrastructure and enhancing the capacity to withstand natural disasters [42,46]. Thus, EIAP will also be influenced.

As for the data and variables, there are some points deserving special attention: 1) Agricultural added value and fiscal expenditure are deflated at 1991 constant prices; 2) there is only the data of total consumption in primary industry; hence, the proportion of agricultural added value to added value of primary industry is used as a proxy of the proportion of DECAP to direct energy consumption of primary industry; 3) IECAP is the total consumption of energy used for the production of applied chemical fertilizers and pesticides, and conversion coefficients from chemical fertilizers and pesticides to energy can be obtained from China Energy Statistical Yearbook; and 4) there is only data of the labor force of primary industry, and the proportion of agricultural added value to added value of primary industry is used as a proxy of the proportion of agricultural labor force to labor force of primary industry. The data sources include China Energy Yearbook, China Statistical Yearbook, China Population and Employment Statistical Yearbook, China Rural Statistical Yearbook, China Agriculture Statistical Report, and Finance Yearbook of China.

Table 2 lists summary statistics of the variables in the dataset that cover 30 provinces in China from 1991–2016. On average, EIAP, DEIAP, and IEIAP are 1.02 tce/10,000 CNY, 0.61 tce/10,000 CNY and 0.41 tce/10,000 CNY, respectively; the average sown area of vegetable accounts for 12% of China's total sown area, and the average retail price index of fuels is 3.72. Besides, the logarithmic forms of income and fiscal expenditure are adopted, which are 8.67 and 12.40, on average and respectively, and the average old dependency ratio reached 0.12 in rural China. Further, labor force and machinery, used as agricultural inputs and on average, are 1.18 persons/hectare and 4.34 kilowatt/hectare, respectively.

Table 2. Summary statistics for variables.

Variable	Unit	Definition	Mean	S. D.	Min	Max
EIAP	tce/10,000 CNY	Ratio of energy intensity of agricultural production to agricultural added value	1.02	0.46	0.25	5.10
DEIAP	tce/10,000 CNY	Ratio of direct energy intensity of agricultural production to agricultural added value	0.61	0.25	0.18	1.78
IEIAP	tce/10,000 CNY	Ratio of indirect energy intensity of agricultural production to agricultural added value	0.41	0.34	0.05	4.16
Structure	ratio	Ratio of vegetable sown area to total sown area	0.12	0.08	0.01	0.41
Price	ratio	Rural retail price index of fuels	3.72	2.12	1.00	10.62
Income	log	Agricultural added value per labor	8.67	0.76	6.98	10.33
Labor	person/hectare	Agricultural labor force input per hectare of sown area	1.18	0.42	0.27	2.63
Dependency	ratio	The ratio of rural population aged over 65 to population aged 15–64	0.12	0.04	0.05	0.31
Fiscal expenditure	log	Government's fiscal expenditure on agriculture	12.40	1.35	9.55	15.10
Machinery	kilowatt/hectare	Agricultural machinery power per unit of sown area	4.34	2.78	0.00	21.73
East	Dummy variable	East area	0.40	0.49	0	1
Central	Dummy variable	Central area	0.30	0.46	0	1
West	Dummy variable	West area	0.29	0.46	0	1
SSR	Dummy variable	South & Southwest Region	0.13	0.34	0	1
YRB	Dummy variable	Yangtze River Basin	0.27	0.44	0	1
LP	Dummy variable	Loess Plateau	0.17	0.37	0	1
YGP	Dummy variable	Yunnan-Guizhou Plateau	0.07	0.25	0	1
NHR	Dummy variable	Northern High-Latitude Region	0.13	0.34	0	1
HCP	Dummy variable	Huang-Huai-Hai & Circum-Bohai-Sea Plain	0.23	0.42	0	1

Data source: Authors' own calculation.

4. Results and Discussion

Pooled regression is not applied in this study because the least square estimators are inconsistent due to individual province effects. With this in mind, the fixed-effect estimators and random-effect estimators are adopted in this study. A fixed-effect model hypothesizes that the residuals composed of the unobservable regional effect are related to the independent variables, while a random-effect model hypothesizes that the residuals composed of the unobservable regional effects are randomly distributed and strictly independent of the independent variables [108]. The Hausman test rejected the null hypothesis under which the random-effect estimators are consistent; hence, the fixed-effect estimators are consistent in this study, although not necessarily efficient. Table 3 reports the estimation results for Equation (1), which focuses on the national trend. Table 4 reports the estimation results for Equations (2) and (3), which considers regional heterogeneity.

Table 3. Estimation results for Equation (1).

	(1)	(2)	(3)	(4)	(5)	(6)
	EIAP	EIAP	IEIAP	IEIAP	DEIAP	DEIAP
Structure	0.983 ** (2.93)	1.083 *** (3.39)	1.216 *** (4.45)	1.123 *** (4.14)	−0.228 (−1.62)	−0.0366 (−0.28)
Price		−0.155 *** (−9.33)		−0.109 *** (−7.72)		−0.0463 *** (−6.86)
Income		−0.628 *** (−6.92)		−0.182 * (−2.36)		−0.446 *** (−12.08)
Labor		−0.328 *** (−4.21)		−0.0531 (−0.80)		−0.274 *** (−8.66)
Dependency		1.974 *** (3.81)		1.192 ** (2.71)		0.781 *** (3.71)
Fiscal expenditure		−0.0487 (−1.24)		−0.0818 * (−2.45)		0.0331 * (2.07)
Machinery		−0.00674 (−0.74)		−0.00931 (−1.20)		0.00275 (0.74)
Constant	1.300 *** (24.06)	7.231 *** (8.15)	0.470 *** (10.68)	2.909 *** (3.86)	0.830 *** (36.64)	4.320 *** (12.00)
R ²	0.5019	0.5929	0.1836	0.2736	0.7068	0.7751
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Province effect	Yes	Yes	Yes	Yes	Yes	Yes
Observation	780	780	780	780	780	780

Note: *t* statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Estimation results for Equations (2) and (3).

	(1)	(2)	(3)	(4)	(5)	(6)
	EIAP	EIAP	IEIAP	IEIAP	DEIAP	DEIAP
Structure*East	0.992 ** (3.11)		1.107 *** (4.06)		−0.112 (−0.88)	
Structure*Middle	−0.110 (−0.12)		1.291 (1.63)		−1.389 *** (−3.78)	
Structure*West	2.358 *** (3.55)		1.581 ** (2.78)		0.801 ** (3.03)	
Structure*SSR		1.587 ** (3.12)		1.295 ** (3.00)		0.296 (1.46)
Structure*YRB		1.093 ** (2.82)		1.492 *** (4.53)		−0.394 * (−2.55)
Structure*LP		0.300 (0.31)		1.643 * (1.99)		−1.307 *** (−3.37)
Structure*YGP		−0.0338 (−0.03)		−0.760 (−0.75)		0.740 (1.57)

Table 4. Cont.

	(1)	(2)	(3)	(4)	(5)	(6)
	EIAP	EIAP	IEIAP	IEIAP	DEIAP	DEIAP
Structure*NHR		6.028 *		3.764		2.268 *
		(2.53)		(1.86)		(2.39)
Structure*HCP		0.315		0.296		0.0237
		(0.55)		(0.60)		(0.10)
Price	−0.155 ***	−0.132 ***	−0.109 ***	−0.0867 ***	−0.0460 ***	−0.0459 ***
	(−9.35)	(−6.57)	(−7.70)	(−5.07)	(−7.00)	(−5.71)
Income	−0.633 ***	−0.618 ***	−0.181 *	−0.212 **	−0.452 ***	−0.406 ***
	(−6.99)	(−6.48)	(−2.33)	(−2.62)	(−12.56)	(−10.69)
Labor	−0.315 ***	−0.355 ***	−0.0409	−0.119	−0.273 ***	−0.236 ***
	(−3.94)	(−3.70)	(−0.60)	(−1.46)	(−8.59)	(−6.17)
Dependency	1.556 **	2.149 ***	1.051 *	1.104 *	0.499 *	1.046 ***
	(2.85)	(3.88)	(2.25)	(2.35)	(2.30)	(4.74)
Fiscal expenditure	−0.0621	−0.0571	−0.0877 *	−0.0982 **	0.0253	0.0409 *
	(−1.56)	(−1.41)	(−2.57)	(−2.86)	(1.60)	(2.54)
Machinery	−0.00502	0.000418	−0.00865	−0.00224	0.00384	0.00283
	(−0.55)	(0.04)	(−1.11)	(−0.27)	(1.06)	(0.72)
Constant	7.434 ***	7.228 ***	2.949 ***	3.389 ***	4.484 ***	3.841 ***
	(8.40)	(7.64)	(3.90)	(4.22)	(12.75)	(10.19)
R ²	0.5982	0.5980	0.2744	0.2845	0.7874	0.7864
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Province effect	Yes	Yes	Yes	Yes	Yes	Yes
Observation	780	780	780	780	780	780

Note: *t* statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.1. The Influence of ASC on EIA-National Trend

In Table 3, columns (1), (3), and (5) show the regression results only considering ASC, and columns (2), (4), and (6) control additional variables that may influence energy intensity. The sown proportion of vegetable improves EIAP and IEIAP significantly, while its impact on DEIAP is negative and insignificant. Conclusions can be drawn that ASC improve China's EIAP mainly through DEIAP, ASC decrease EIAP through IEIAP. Our result is in accordance with the results of most previous studies relating to economic structure and overall energy intensity [54–64], that is, the larger the proportion of the added value of energy-intensive industry to GDP, the higher the aggregate energy intensity. Similarly, the result can be explained by the structural effect.

The basic assumption underlying the structural effect is that the energy intensity of secondary industry is larger than that of primary industry or tertiary industry [92]. With the advancement of national industrialization, the proportion of the added value of secondary industry rises, thereby enhancing aggregate energy intensity [61]. In China, the rising income has induced significant changes in people's dietary habit since 1978, and people demand for more vegetable, fruit, and other commercial crops rather than grain crops [49]. For instance, the proportion of grain expenditure to total food expenditure decreased from 63.75% to 51.71% during 1991–2016. In response to the changing market demand, significant structural changes have occurred in China's agricultural sector [9,29]. ASC in China derive from two sources. For one thing, there is a counter-balance paradox between the sown proportions of grain crops and vegetable. In other words, a significant proportion of area, once used to grow grain crops, is now used to cultivate commercial crops, among which vegetable accounts for a large proportion. For instance, the sown area used for cultivating grain crops decreased from 112.31 million hectares to 99.41 million hectares during 1991–2003. For another thing, due to increasing market demand, the sown area of vegetable increased from 6.55 million hectares to 22.33 million hectares, thereby facilitating ASC.

Induced by economic benefits and due to comparatively high value of vegetable, more and more arable land in China is used for commercial crops like vegetable. Compared to grain crops, the cultivation of vegetable requires more application of chemical fertilizers and pesticides, leading to an increase of IECAP in China [31]. During 1994–2016, the weighted fertilizing amount of grain crops increased from 181.95 kg/hectare to 312.60 kg/hectare, with an average annual growth rate of 2.49%, while that of vegetable increased from 292.05 kg/hectare to 552.60 kg/hectare, with an average annual growth rate of 2.94% (see Figure 6). Regardless of the violent fluctuation of the weighted fertilizing amount of vegetable, the fertilizing amount of vegetable is much larger than that of grain crops. Considering that IECAP is the major form of ECAP in China, the increasing proportion of vegetable significantly leads to the increase of EIAP.

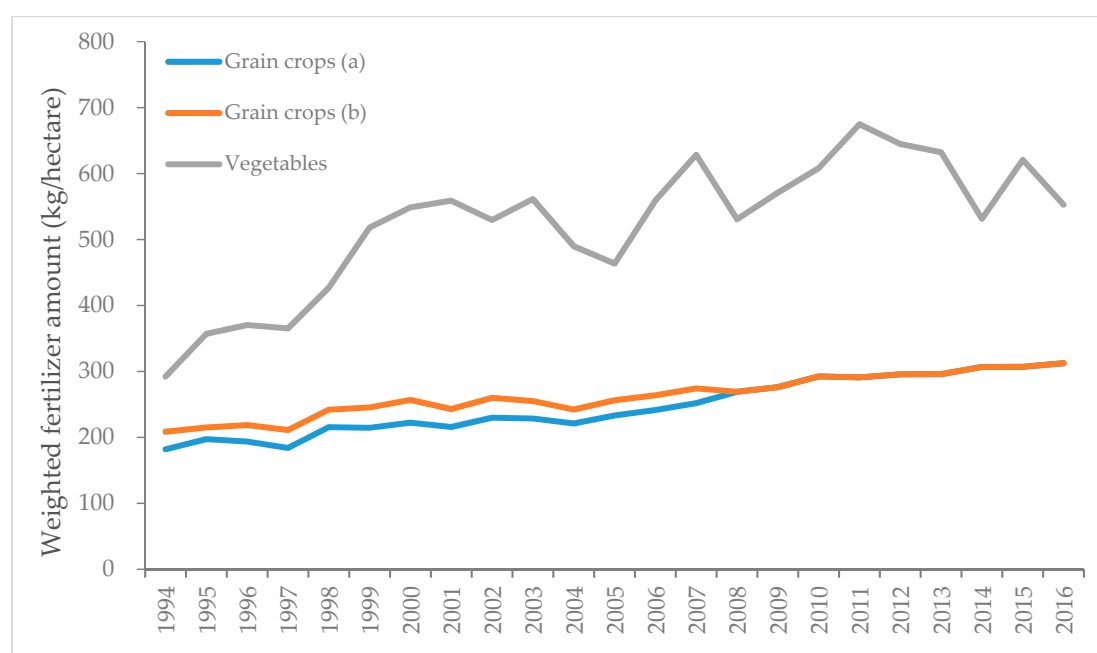


Figure 6. The weighted fertilizing amount of grain crops and vegetable in 1994 and 2016. Note: (1) we adopt the data of 1994–2016 due to data missing during 1991–1993; (2) the average fertilizing amount of sorghum and millet hasn't been published after 2007, so the index of Grain crops (a) considers sorghum and millet and the index of Grain crops (b) doesn't consider sorghum and millet; and (3) following the method adopted by the National Agricultural Products Cost-benefit Data Compilation, the weighted coefficient is the arithmetic average proportion of each crop. (Data source: [109]).

One in particular is that ASC improves China's EIAP through DEIAP rather than IEIAP, which may be explained by different planting modes of different crops in China. As commercial crops like vegetable and fruit require more procedures from planting to picking and are characterized by storage difficulty and pressure intolerance, the mechanization degree for those crops is far from enough [110]. In fact, the mechanization rate for vegetable is less than 20% in China, while that for wheat, rice, and maize is 93.21%, 68.82%, and 75.95%, respectively [111]. In addition, the cultivation of vegetable in China is still dominated by the smallholder business model, resulting in the high cost of mechanized operation costs and inapplicability of large-scale agricultural machinery. The degree of mechanization of grain crops is much higher than that of vegetable [112]. Hence, the influence of ASC on DEIAP is insignificant.

4.2. The Influence of ASC on EIA-Regional Heterogeneity

This paper employs two types of regional groupings, and our empirical results show that the impact of ASC reveals significant regional heterogeneity. Columns (1), (3), and (5) in Table 4 show the

regression results considering regional heterogeneity in terms of administrative division of regions. It is observed that the impact of ASC in East Region, Central Region, and West Region is generally in line with that of national trend, that is, the sown proportion of vegetable influences EIAP and IEIAP significantly and positively, while its impact on DEIAP is negative and insignificant; except for the impact of ASC on DEIAP in West Region, and the impact of ASC on EIAP and DEIAP in Middle Region.

The significantly positive impact of ACS on EIAP and IEIAP can be explained by the aforementioned structural effect, while the exception may be due to different levels of vegetable mechanization in different regions. Specifically, the mechanization level for vegetable production shows an increasing trend from East Region through Central Region to West Region due to different concentration degrees of vegetable industry, landform, and other natural conditions [113]. For instance, Shouguang City in East Region is mostly flat with few hills and has a long history for vegetable cultivation, which are beneficial for the massive application of advanced equipment such as seeders and vegetable cleaning equipment. However, limited by complicated topographic features and a labor structure dominated by female and the old, there are limited uses of vegetable machinery in West Regions [114]. Different levels of mechanization lead to different impact levels of ASC on DEIAP. In other words, the comparatively high level of mechanization in East Region and Central Region brings the scale economy effect of DECAP, thereby decreasing DEIAP, and the comparatively low level of mechanization in West Region brings the incremental effect of DECAP, thereby increasing DEIAP. Due to the lower level of mechanization in Middle Region than that in East Region, the scale economy effect is more significant in Middle Region, which explains the larger absolute value of the coefficient in Middle Region than that in East Region.

The coefficients of ASC on IEIAP reveal an increasing trend from East Region through Central Region to West Region, which may be explained by the scale economy effect of fertilizer application. Both the current sown proportion of vegetable and ASC during 1991–2016 show a decreasing trend from East Region through Central Region to West Region (see Figure 2). At the same time of leading to different levels of IEIAP in different regions, different levels of ASC bring the scale economy effect, that is, the rising sown proportion of vegetable tends to decrease IEIAP. The regional heterogeneity may be explained by different changing amplitudes of agricultural structure in different regions. The sown proportion of vegetable between 1991 and 2016 varies significantly among East Region, Central Region, and West Region (see Figure 2). The amplitude of ASC among different regions is in line with the empirical results. In other words, the higher the amplitude of ASC, the larger the scale economy effect, which explains the increasing coefficients of IEAP from East Region through Central Region to West Region.

Columns (2), (4), and (6) in Table 4 show the regression results considering regional heterogeneity in terms of the six vegetable production regions. The results in South and Southwest Region and Yangtze River Basin are in accordance with that in East Region. As most provinces in South and Southwest Region are provinces in East Region, the aforementioned structural effect can account for the significantly positive impact of ACS on EIAP and IEIAP, and different mechanization levels of vegetable production can be used to illustrate the variance of the impact of ASC on DEIAP. In the plain areas with better economic conditions, like South and Southwest Region, the mechanization of vegetable production is acceptable, and the mechanized operations mainly exist in the procedures of soil ploughing and preparation and crop protection [115], which explains why the influence of ASC in DEIAP is insignificant. Besides, despite the provinces classified into Yangtze River Basin covering provinces in East Region, Central Region, and West Region, they are all developed provinces in China. Benefiting from comparatively high level of vegetable mechanization and high income, vegetable producers in those provinces are able to upgrade vegetable machinery, such as harvesting machinery, soil ploughing and preparation machinery, and vegetable protection machinery [115], thereby significantly decreasing DEIAP.

Influenced by topographic conditions and economic conditions, the mechanization of vegetable in Yunnan-Guizhou Plateau is relatively backward and the development of mechanization is limited [116]. In the hilly and mountainous areas of Yunnan-Guizhou Plateau, in addition to the mechanization of plant protection (some of which are still driven by manpower), the cultivation of vegetable is basically dependent on labor, and the level of mechanization is very low [115]. Similarly, the incremental effect of ASC induced by the low and limited level of mechanization in Yunnan-Guizhou Plateau improves DEIAP, but the impact is insignificant. The result in Northern High-Latitude Region and Loess Plateau can be attributed to the changes of the scales of vegetable producers [117]. The most significant growth of large vegetable producers has been witnessed in Northern High-Latitude Region and Loess Plateau during 2010–2016, whose growth rate are 28% and 20% [117]. Compared to small vegetable producers, large vegetable producers are more likely and able to adopt agricultural machinery. Due to the comparatively lower mechanization degree of Northern High-Latitude Region than that of Loess Plateau, the adoption of agricultural machinery brings incremental effect of DEIAP in Northern High-Latitude Region, and brings scale economy effect of DEIAP in Loess Plateau.

Different from the outdoor cultivation of vegetable in other five regions, greenhouse vegetable has been massively promoted in Huang-Huai-Hai and Circum-Bohai-Sea Plain [99]. Compared to outdoor vegetable production, greenhouse cultivation is dependent on the large sources of direct and indirect energy [118]. However, the impact of ASC on EIAP, DEIAP, and IEIAP is insignificantly positive in China, which may be attributed to two reasons. As for IEIAP, despite that greenhouse vegetable systems are featured by initial high input of nutrients, those systems maintain similar soil fertility [116,119], which limitedly increases IEIAP. As for DEIAP, the cultivation of greenhouse vegetable in China is still labor-intensive [120], and therefore, the impact of ASC on IEIAP is insignificant.

4.3. EIAP and Other Determinants

Consistent with most previous studies [59,67,92], the coefficient of energy price is significantly negative as agricultural producers respond to the rising energy price by improving energy efficiency. However, the result is contrary to the findings [100,101] that in rural China, energy prices cannot reflect the real demand and supply of the energy market due to energy-price regulation. The difference between agricultural energy consumption and residential energy consumption in rural China may be explained by different levels of price regulation on different energies and different commercialization degrees of different energies. While the regulations on coal and oil were abolished in the 1990s, there are still some constraints on electricity tariffs [121]. Hence, the change of energy price varies in different energies and reflects market demand and supply to a certain degree. In 2014, rural residential energy mix includes straw (37.15%), firewood (21.00%), biogas (3.44%), coal (18.26%), oil (5.05%), liquid petroleum gas (2.72%), and electricity (12.38) [100], while agricultural production energy mix contains coal (32.63%), gasoline (5.74%), diesel (39.18%), and electricity (22.45%). It is seen that agricultural energy achieves complete commercialization, while rural residential energy relies heavily on biomass resources.

The significantly negative impact of income on energy intensity has been verified in China in most studies [67,71,96], and the empirical result confirms such impact in the China's agricultural sector. As China's agriculture becomes more developed, its energy efficiency improves and energy intensity falls, which may be attributed to two mechanisms. For one thing, with the improvement of income level, people's attitude towards environment or natural resources arises [71], and the rising environmental awareness contributes to the efficient utilization of machinery fuels, chemical fertilizers, and pesticides. Hence, its impact on EIAP, DEIAP, and IEIAP is significantly negative. For another thing, agricultural producers are able to afford or upgrade more energy-efficient agricultural machinery as per capita income rises, thereby contributing to the decline of EIAP, DEIAP, and IEIAP.

The empirical result shows that agricultural labor force facilitates the decline of EIAP and DEIAP significantly, and its impact on IEIAP is negative, but insignificant, which can be explained by the substitution effect between energy and labor force. Through estimating total cost function and energy

share formulas, labor force is proved to be a substitute for energy in China [122]. However, such impact may be disadvantageous for reducing EIAP because agricultural labor force has been declining for decades due to urbanization and labor migration. Another finding relating to agricultural labor force is that the aging population significantly improves EIAP, IEIAP, and DEIAP. The potential explanation is that other further agricultural inputs including chemical fertilizers, pesticides, and machinery are adopted to make up for the deficiencies of the aging agricultural labor force [115].

Fiscal investment from Chinese government decreases IEIAP and increases DEIAP significantly, which is related to its purposes. Of fiscal investment, a large proportion is used for agricultural fixed assets such as agricultural machinery, which consume energy directly. As can be seen in Tables 3 and 4, the effects of agricultural mechanization on EIAP and DEIAP are not obvious. On the one hand, the equipment structure of agricultural machinery is unreasonable, and it is inefficiently used, resulting in that the growth of agricultural output is lower than that of EACP [67]; hence, DEIAP tends to rise. On the other hand, agricultural mechanization is still low in China and the energy used by agricultural machinery only accounts for a small proportion of ECAP, which means it is insufficient to decrease EIAP significantly.

4.4. Further Discussion

Robustness is examined as follows: according to the approach of robustness checks through “examining how certain ‘core’ regression coefficient estimates behave when the regression specification is modified in some way, typically by adding or removing regressors” [123], the stepwise regress is employed, and the core variable and control variables are successively added to test the plausible signs and magnitudes of the estimated regression coefficients [124]. Comparing Tables 3 and 4, it is shown that the empirical results are robust.

Reverse causality is one significant fact that may lead to the endogenous problem, which exists in the research relating to energy consumption and energy prices. In other words, consumers make their consumption decisions according to the current price, while the consumption codetermines current price with other factors. However, it is believed that energy price is an exogenous variable for agricultural consumption because, although the energy market in China is not a perfectly competitive market, its agricultural producers can be treated as price-takers. From the perspective of agricultural electricity, its price have been regulated at a lower level and is not allowed to adjust quickly [102,125]. Power plants in China face market-oriented prices for their inputs, mainly coal, while their output needs to follow the mandatory price. For instance, coal price increased by 80% during 2007 and mid-2011, but the electricity price was only allowed to increase by 15% [125]. Besides, there exists an electricity price subsidy for agriculture, which further lowers the electricity price. The electricity price for small and medium chemical fertilizer plants is 0.357 CNY/kilowatt-hour, while the price for residential purposes is 0.4883 CNY/kilowatt-hour [126].

While the prices of coal, gasoline, and diesel adjust according to changes in the international fossil fuels prices to a certain degree and are more market-oriented when compared to electricity price, Chinese government still regulates those prices [102]. Those measures aim to reduce the fast-growing input cost for farmers and support the development of rural economy [126]. In addition, agricultural energy consumption accounts for a small proportion of overall energy consumption and consumers are scattered across China, which further decreases their bargaining power on energy prices. Consequently, to some degree, it is believed that there exists no reverse causation between agricultural energy consumption and energy prices.

5. Conclusions and Policy Implications

China’s agricultural structure has undergone significant changes for the past four decades, as has its agricultural energy consumption. To achieve sustainable agricultural growth, it is important to investigate the impact China’s ASC on energy consumption. On the national level, ASC is characterized by the fall of sown proportion of grain crops and the rise of vegetable, and EIAP, DEIAP, and IEIAP all

reveal a decreasing trend. Employing the panel data on 30 provinces during 1991–2016, this paper investigates the impact of ASC on EIAP, DEIAP, and IEIAP in China. On the provincial level, ASC, EIAP, DEIAP, and IEIAP reveal significant regional heterogeneity. Adopting two division standards, we further analyze the role of regional ASC on EIAP, DEIAP, and IEIAP in terms of the administrative division of regions and the six vegetable production regions. Further, some key factors influencing agricultural energy intensity are distinguished. The main conclusions are as follows.

The empirical results show that: (1) ASC increase EIAP and IEIAP significantly, while its impact on DEIAP is negative and insignificant, which may be explained by the structural effect and different planting modes of different crops; (2) the impact in the three administrative regions is similar to national situation, except the impact of ASC in DEIAP in West Region, which can be explained by different mechanization levels of vegetable production in different regions; (3) compared to the administrative division of regions, the results of the six vegetable production regions reveal greater regional heterogeneity, and this is attributed to the scale economy effect and the incremental effect of different levels of mechanization for vegetable production; and (4) fuel price, per capita income, agricultural labor forces, old dependency ratio, and government fiscal income are verified to disproportionately affect EIAP, DEIAP, and IEIAP. According to the empirical results, there are four policy implications.

Firstly, this paper finds out that ASC in China increase EIAP through the channel of IEIAP, and the utilization of chemical fertilizers and pesticides is directly related to IEIAP. However, the recent agricultural planning from Chinese government shows that the trend of ASC will be maintained, implying that ASC will further facilitate the improvement of EIAP and IEIAP. As the non-point pollution is getting worse, it is important to control the extensive application of chemical fertilizers and pesticides on vegetable production. To be specific, the policy tools include enhancing utilization efficiency of chemical inputs, encouraging the utilization of organic manure such as agricultural straw and animal wastes, and improving the environmental awareness of the agricultural labor forces.

Secondly, the level of vegetable mechanization in China should be further improved. As the second largest crop in China, its mechanization level is much lower than that of grain crops. The empirical result has proved the insignificantly negative impact of ASC on DEIAP, and the impact ASC varies in different regions, which is attributed to the scale economy effect and the incremental effect induced by different levels of mechanization for vegetable production. In order to change the incremental effect into the scale economy effect, it is necessary to further improve vegetable mechanization and the specific countermeasures include agricultural subsidies for purchasing vegetable machinery, improving the proportion of large vegetable producers and increasing the mechanization of different vegetable production procedures.

Thirdly, the impact and significance of ASC on EIAP, DEIAP, and IEIAP varies among three administrative regions and six vegetable production regions, which is disadvantageous for balancing regional EIAP and decreasing national EIAP. While regional agricultural structure is difficult to be changed since it is a result of socioeconomic, political, and natural factors, government policies should pay more attention to balance regional agricultural structure, such as promoting agricultural product circulation and transferring planting farming among regions.

Fourthly, from the perspective of the impact of control variables on EIAP, there are several implications. From the perspective of rural labor, the aging and decreasing rural labor force is disadvantageous for the decline of EIAP. Hence, more policy attention should be paid to improving the quality and quantity of agricultural labor force. In addition, more fiscal expenditure should be allocated to agriculture to promote the level of agricultural mechanization.

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References

1. Lin, J.Y. Rural reforms and agricultural growth in China. *Am. Econ. Rev.* **1992**, *82*, 34–51.
2. Lin, J.Y. Endowments, technology, and factor markets: A natural experiment of induced institutional innovation from China's rural reform. *Am. J. Agric. Econ.* **1995**, *77*, 232–242. [[CrossRef](#)]
3. Qiao, Z.; Jiao, F.Y.; Li, N. Change of rural institution and agricultural economic growth: An empirical analysis on agricultural economic growth in China. *Econ. Res. J.* **2006**, *7*, 73–82. (In Chinese)
4. Huang, J.; Rozelle, S. Technological change: Rediscovering the engine of productivity growth in China's rural economy. *J. Dev. Econ.* **1997**, *49*, 337–369. [[CrossRef](#)]
5. Chen, P.C.; Yu, M.M.; Chang, C.C.; Hsu, S.H. Total factor productivity growth in China's agricultural sector. *China Econ. Rev.* **2008**, *19*, 580–593. [[CrossRef](#)]
6. Liu, S.W.; Zhang, P.Y.; He, X.L.; Li, J. Efficiency change in North-East China agricultural sector: A DEA approach. *Agric. Econ.* **2015**, *61*, 522–532. [[CrossRef](#)]
7. Ito, J. Inter-regional difference of agricultural productivity in China: Distinction between biochemical and machinery technology. *China Econ. Rev.* **2010**, *21*, 394–410. [[CrossRef](#)]
8. Ma, L.; Velthof, G.L.; Wang, F.H.; Qin, W.; Zhang, W.F.; Liu, Z.; Zhang, Y.; Wei, J.; Lesschen, J.P.; Ma, W.Q.; et al. Nitrogen and phosphorus use efficiencies and losses in the food chain in China at regional scales in 1980 and 2005. *Sci. Total. Environ.* **2012**, *434*, 51–61. [[CrossRef](#)]
9. Wu, H.J.; Wang, S.; Gao, L.M.; Zhang, L.; Yuan, Z.W.; Fan, T.Y.; Wei, K.P.; Huang, L. Nutrient-derived environmental impacts in Chinese agriculture during 1978–2015. *J. Environ. Manag.* **2018**, *217*, 762–764. [[CrossRef](#)]
10. Yang, J.; Huang, Z.H.; Zhang, X.B.; Reardon, T. The rapid rise of cross-regional agricultural mechanization services in China. *Am. J. Agric. Econ.* **2013**, *95*, 1245–1251. [[CrossRef](#)]
11. Gong, B. Agricultural reforms and production in China: Changes in provincial production function and productivity in 1978–2015. *J. Dev. Econ.* **2018**, *132*, 18–31. [[CrossRef](#)]
12. Lin, B.Q.; Fei, R.L. Analyzing inter-factor substitution and technical progress in the Chinese agricultural sector. *Eur. J. Agron.* **2015**, *66*, 54–61. [[CrossRef](#)]
13. Fei, R.L.; Lin, B.Q. Energy efficiency and production technology heterogeneity in China's agricultural sector: A meta-frontier approach. *Technol. Forecast. Soc. Chang.* **2016**, *109*, 25–34. [[CrossRef](#)]
14. Fei, R.L.; Lin, B.Q. Estimates of energy demand and energy saving potential in China's agricultural sector. *Energy* **2017**, *135*, 865–875. [[CrossRef](#)]
15. Fluck, R.C. *Energy Analysis for Agricultural Systems—a Volume in Energy in World Agriculture*; Elsevier Science Ltd.: Amsterdam, The Netherlands, 1992; ISBN 978-0-444-88681-1.
16. Yu, J.L.; Wu, J. The sustainability of agricultural development in China: The agriculture–environment nexus. *Sustainability* **2018**, *10*, 1776. [[CrossRef](#)]
17. Li, Q.; Yang, W.J.; Li, K. Role of social learning in the diffusion of environmentally-friendly agricultural technology in China. *Sustainability* **2018**, *10*, 1527. [[CrossRef](#)]
18. Guo, J.H.; Liu, X.J.; Zhang, Y.; Shen, J.L.; Han, W.X.; Zhang, W.F.; Christie, P.; Goulding, K.W.T.; Vitousek, P.M.; Zhang, F.S. Significant acidification in major Chinese croplands. *Science* **2010**, *327*, 1008–1010. [[CrossRef](#)]
19. Norse, D.; Ju, X.T. Environmental costs of China's food security. *Agric. Ecosyst. Environ.* **2015**, *209*, 5–14. [[CrossRef](#)]
20. Guan, X.L.; Zhang, J.B.; Wu, X.R.; Cheng, L.L. The shadow prices of carbon emission in China's planting industry. *Sustainability* **2018**, *10*, 753. [[CrossRef](#)]
21. MEP. Bulletin on the First National Census on Pollution Sources. 2010. Available online: <http://cpsc.mep.gov.cn/gwgg/201002/W020100225545523639910.pdf> (accessed on 9 November 2018). (In Chinese)
22. Li, J.H.; Jing, Y.P. The impacts of rural economic structure dynamics on agricultural energy efficiency. *Issues Agric. Econ.* **2011**, *11*, 93–99. (In Chinese)
23. SAIN. Improved Nutrient Management in Agriculture—a Neglected Opportunity for China's Low Carbon Growth Path. Available online: [www.sainonline.org/SAINwebsite\(English\)/download/PolicyBriefNo1final.pdf](http://www.sainonline.org/SAINwebsite(English)/download/PolicyBriefNo1final.pdf) (accessed on 9 November 2018).
24. SAIN. Improving Manure Nutrient Management Towards Sustainable Intensification in China. 2012. Available online: [http://www.sainonline.org/SAIN-Website\(English\)/download/SAIN_Policy_Brief_No6_EN.pdf](http://www.sainonline.org/SAIN-Website(English)/download/SAIN_Policy_Brief_No6_EN.pdf) (accessed on 9 November 2018).

25. IPCC. *Climate Change 2007: Synthesis Report*; Cambridge University Press: Cambridge, UK, 2007; ISBN 92-9169-122-4.
26. Fei, R.L.; Lin, B.Q. The integrated efficiency of inputs–outputs and energy-CO₂ emissions performance of China’s agricultural sector. *Renew. Sustain. Energy Rev.* **2016**, *75*, 668–676. [[CrossRef](#)]
27. CCCPC; SC. Opinions on Implementing the Rural Revitalization Strategy. Available online: http://www.gov.cn/zhengce/2018-02/04/content_5263807.htm (accessed on 9 November 2018). (In Chinese)
28. Tan, R.P.; Lin, B.Q. What factors lead to the decline of energy intensity in China’s energy intensive industries? *Energy Econ.* **2018**, *71*, 213–221. [[CrossRef](#)]
29. Liu, Y.Q.; Song, W.; Mu, F.Y. Changes in ecosystem services associated with planting structures of cropland: A case study in Minle County in China. *Phys. Chem. Earth Parts A/B/C* **2017**, *102*, 10–20. [[CrossRef](#)]
30. Canakci, M.; Akinci, I. Energy use pattern analyses of greenhouse vegetable production. *Energy* **2006**, *31*, 1243–1256. [[CrossRef](#)]
31. Xin, L.J.; Li, X.B.; Tan, M.H. Temporal and regional variations of China’s fertilizer consumption by crops during 1998–2008. *J. Geogr. Sci.* **2012**, *22*, 643–652. [[CrossRef](#)]
32. Dong, S. Declining energy intensity in the U.S. agricultural sector: Implications for factor substitution and technological change. *Sustainability* **2015**, *7*, 13192–13205.
33. Bruinsma, J. The Resources Outlook to 2050: By How Much do Land, Water and Crop Yields Need to Increase by 2050? Available online: <http://www.fao.org/3/a-ak971e.pdf> (accessed on 9 November 2018).
34. Xing, H.; Zhao, Y.; Wang, Y.Q. Temporal and spatial analysis of regional differences of the agricultural energy consumption in China. *Chin. Agric. Sci. Bull.* **2014**, *30*, 95–101. (In Chinese)
35. Liu, X.H. Preliminary study on energy conversion efficiency of farmland in different regions of China. *J. China Agric. Univ.* **1982**, *1*, 1–20. (In Chinese)
36. Li, L.H. Discussion on the analysis index of energy flow in agro-ecosystem. *Res. Agric. Mod.* **1988**, *1*, 18–19. (In Chinese)
37. Li, L.L.; Huang, Y.Z.; Han, C.R. A reconsideration of conversion factors for calculating industrial energy input in agroecosystems. *Rural. Eco-Environ.* **1989**, *4*, 32–36. (In Chinese)
38. Yu, Z.X.; Li, N.; Mu, H.L.; Jiang, Y.Q. Empirical study on the regional agricultural energy efficiency convergence across provinces in China. *Energy Procedia* **2017**, *142*, 2391–2396. [[CrossRef](#)]
39. Hu, L.L.; Niu, S.W.; Ma, L.; Qin, J. The agricultural energy use and economic benefits in China. *J. Arid. Land Resour. Environ.* **2011**, *25*, 1–6. (In Chinese)
40. Zhu, L.Z.; Liu, J.; Xiang, M. Analysis on the change and trend of agricultural production energy consumption in China. *Environ. Econ.* **2010**, *12*, 44–47. (In Chinese)
41. Li, N.; Mu, H.L.; Li, H.N.; Gui, S.S. Diesel consumption of agriculture in China. *Energies* **2012**, *5*, 5126–5149. [[CrossRef](#)]
42. Peng, K.; An, Y.F. Empirical study on influential factors of energy consumption for agricultural production in China: Based on fixed-effect model. *Technol. Econ.* **2012**, *31*, 101–106. (In Chinese)
43. Xing, H.; Zhao, Y.; Wang, Y.Q. Regional disparities and its influence factors of agricultural energy consumption on county scale in Nantong city. *J. Nanjing Norm. Univ.* **2015**, *38*, 127–134. (In Chinese)
44. Xie, S.J. Analysis on carbon emissions from energy consumption in agricultural and reduction measures in Guangdong province. *J. Anhui Agric. Sci.* **2011**, *39*, 1751–1754. (In Chinese)
45. Xu, J.P. China’s agricultural energy consumption and CO₂ emissions: Current situation, trend and path to reduce emissions. *Ecol. Econ.* **2016**, *2*, 122–126. (In Chinese)
46. Fei, R.L.; Lin, B.Q. Technology gap and CO₂ emission reduction potential by technical efficiency measures: A meta-frontier modeling for the Chinese agricultural sector. *Ecol. Indic.* **2017**, *73*, 653–661. [[CrossRef](#)]
47. Chenery, H.B.; Syrquin, M.; Elkington, H. *Patterns of Development, 1950 to 1983*; Economic Science Press: Beijing, China, 1988; ISBN 0-8213-1153-0. (In Chinese)
48. NBSC. *China Statistical Yearbook*; China Statistics Press: Beijing, China, 2017; ISBN 978-7-5037-8253-4. (In Chinese)
49. Chen, L.; Wang, J.; Fu, B.; Qiu, Y. Land-use change in a small catchment of northern Loess Plateau, China. *Agric. Ecosyst. Environ.* **2001**, *86*, 163–172. [[CrossRef](#)]
50. Liu, Y.Y. Research on the process and effect of China’s agricultural industry structure adjustment. *Rural. Econ. Sci. Technol.* **2016**, *27*, 71–72. (In Chinese)

51. MOA. *China Agriculture Statistical Report*; China Agriculture Press: Beijing, China, 1992–2017; ISBN 978-7-109-23452-9. (In Chinese)
52. NBSC. *China Energy Statistical Yearbook*; China Statistics Press: Beijing, China, 1992–2017; ISBN 978-7-5037-8437-8. (In Chinese)
53. Dong, K.Y.; Sun, R.J.; Hochman, G.; Li, H. Energy intensity and energy conservation potential in China: A regional comparison perspective. *Energy* **2018**, *155*, 782–795. [[CrossRef](#)]
54. Wei, C.; Ni, J.L.; Shen, M.H. Empirical analysis of provincial energy efficiency in China. *China World Econ.* **2009**, *17*, 88–103. [[CrossRef](#)]
55. Li, Y.; Sun, L.Y.; Feng, T.W.; Zhu, C.Y. How to reduce energy intensity in China: A regional comparison perspective. *Energy Policy* **2013**, *61*, 513–522. [[CrossRef](#)]
56. Jiang, L.; Folmer, H.; Ji, M. The drivers of energy intensity in China: A spatial panel data approach. *China Econ. Rev.* **2014**, *31*, 351–360. [[CrossRef](#)]
57. Li, K.; Lin, B. The nonlinear impacts of industrial structure on China's energy intensity. *Energy* **2014**, *69*, 258–265. [[CrossRef](#)]
58. Ma, B. Does urbanization affect energy intensities across provinces in China? Long-run elasticities estimation using dynamic panels with heterogeneous slopes. *Energy Econ.* **2015**, *49*, 390–401. [[CrossRef](#)]
59. Yan, H. Provincial energy intensity in China: The role of urbanization. *Energy Policy* **2015**, *86*, 635–650. [[CrossRef](#)]
60. Adom, P.K. Determinants of energy intensity in South Africa: Testing for structural effects in parameters. *Energy* **2015**, *89*, 334–346. [[CrossRef](#)]
61. Yang, G.F.; Li, W.L.; Wang, J.L.; Zhang, D.Q. A comparative study on the influential factors of China's provincial energy intensity. *Energy Policy* **2016**, *88*, 74–85. [[CrossRef](#)]
62. Herreras, M.J.; Cuadros, A.; Luo, D. Foreign versus indigenous innovation and energy intensity: Further research across Chinese regions. *Appl. Energy* **2016**, *162*, 1374–1384. [[CrossRef](#)]
63. Huang, J.B.; Du, D.; Hao, Y. The driving forces of the change in China's energy intensity: An empirical research using DEA-Malmquist and spatial panel estimations. *Econ. Modell.* **2017**, *65*, 41–50. [[CrossRef](#)]
64. Huang, J.; Hao, Y.; Lei, H. Indigenous versus foreign innovation and energy intensity in China. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1721–1729. [[CrossRef](#)]
65. Lin, B.Q.; Du, K.R. Decomposing energy intensity change: A combination of index decomposition analysis and production-theoretical decomposition analysis. *Appl. Energy* **2014**, *129*, 158–165. [[CrossRef](#)]
66. Baležentis, A.; Baležentis, T.; Streimikiene, D. The energy intensity in Lithuania during 1995–2009: A LMDI approach. *Energy Policy* **2011**, *39*, 7322–7334. [[CrossRef](#)]
67. Wu, Y. Energy intensity and its determinants in China's regional economies. *Energy Policy* **2012**, *41*, 703–711. [[CrossRef](#)]
68. Okajima, S.; Okajima, H. Analysis of energy intensity in Japan. *Energy Policy* **2013**, *61*, 574–586. [[CrossRef](#)]
69. Chontanawat, J.; Wiboonchutikula, P.; Buddhivanich, A. Decomposition analysis of the change of energy intensity of manufacturing industries in Thailand. *Energy* **2014**, *77*, 171–182. [[CrossRef](#)]
70. Karimu, A.; Brännlund, R.; Lundgren, T.; Söderholm, P. Energy intensity and convergence in Swedish industry: A combined econometric and decomposition analysis. *Energy Econ.* **2017**, *62*, 347–356. [[CrossRef](#)]
71. Song, F.; Zheng, X.Y. What drives the change in China's energy intensity: Combining decomposition analysis and econometric analysis at the provincial level. *Energy Policy* **2012**, *51*, 445–453. [[CrossRef](#)]
72. Farajzadeh, Z.; Nematollahi, M.A. Energy intensity and its components in Iran: Determinants and trends. *Energy Econ.* **2018**, *73*, 161–177. [[CrossRef](#)]
73. Wang, H.; Ang, B.W.; Su, B. Multiplicative structural decomposition analysis of energy and emission intensities: Some methodological issues. *Energy* **2017**, *123*, 47–63. [[CrossRef](#)]
74. Hoekstra, R.; van der Bergh, J.J.C.J.M. Comparing structural and index decomposition analysis. *Energy Econ.* **2003**, *25*, 39–64. [[CrossRef](#)]
75. Liao, H.; Wang, C.; Zhu, Z.; Ma, X. Structural decomposition analysis on energy intensity changes at regional level. *Trans. Tianjin Univ.* **2013**, *19*, 287–292. [[CrossRef](#)]
76. Michel, B. Does offshoring contribute to reducing domestic air emissions? Evidence from Belgian manufacturing. *Ecol. Econ.* **2013**, *95*, 73–82. [[CrossRef](#)]
77. Zeng, L.; Xu, M.; Liang, S.; Zeng, S.; Zhang, T. Revisiting drivers of energy intensity in China during 1997–2007: A structural decomposition analysis. *Energy Policy* **2014**, *67*, 640–647. [[CrossRef](#)]

78. Zhou, X.Y.; Zhou, D.Q.; Wang, Q.W. How does information and communication technology affect China's energy intensity? A three-tier structural decomposition analysis. *Energy* **2018**, *151*, 748–759. [CrossRef]
79. Fan, Y.; Xia, Y. Exploring energy consumption and demand in China. *Energy* **2012**, *40*, 23–30. [CrossRef]
80. Xia, Y.; Yang, C.H.; Chen, X.K. Structural decomposition analysis on China's energy intensity change for 1987–2005. *J. Syst. Sci. Complex.* **2012**, *25*, 156–166. [CrossRef]
81. Zhang, H.Y.; Lahr, M.L. Can the carbonizing dragon be domesticated? Insight from a decomposition of energy consumption and intensity in China, 1987–2007. *Econ. Syst. Res.* **2014**, *26*, 119–140. [CrossRef]
82. Xia, Y.; Fan, Y.; Yang, C.H. Assessing the impact of foreign content in China's exports on the carbon outsourcing hypothesis. *Appl. Energy* **2015**, *150*, 296–307. [CrossRef]
83. Su, B.; Ang, B.W. Multiplicative decomposition of aggregate carbon intensity change using input-output analysis. *Appl. Energy* **2015**, *154*, 13–20. [CrossRef]
84. Su, B.; Ang, B.W. Multi-region comparisons of emission performance: The structural decomposition analysis approach. *Ecol. Indic.* **2016**, *67*, 78–87. [CrossRef]
85. Park, S.H. Decomposition of industrial energy consumption: An alternative method. *Energy Econ.* **1995**, *17*, 265–270.
86. Yuxiang, K.; Chen, Z. Government expenditure and energy intensity in China. *Energy Policy* **2010**, *38*, 691–694. [CrossRef]
87. Zhang, D.; Cao, H.; Wei, Y.M. Identifying the determinants of energy intensity in China: A Bayesian averaging approach. *Appl. Energy* **2016**, *165*, 672–682. [CrossRef]
88. Ma, B.; Yu, Y.H. Industrial structure, energy-saving regulations and energy intensity: Evidence from Chinese cities. *J. Clean. Prod.* **2017**, *141*, 1539–1547. [CrossRef]
89. Fan, R.G.; Luo, M.; Zhang, P.F. A study on evolution of energy intensity in China with heterogeneity and rebound effect. *Energy* **2016**, *99*, 159–169. [CrossRef]
90. Jiang, X.M.; Duan, Y.W.; Green, C. Regional disparity in energy intensity of China and the role of industrial and export structure. *Resour. Conserv. Recycl.* **2017**, *120*, 209–218. [CrossRef]
91. Yuan, C.Q.; Liu, S.F.; Fang, Z.G.; Wu, J.L. Research on the energy-saving effect of energy policies in China: 1982–2006. *Energy Policy* **2009**, *37*, 2475–2480. [CrossRef]
92. Huang, J.B.; Du, D.; Tao, Q.Z. An analysis of technological factors and energy intensity in China. *Energy Policy* **2017**, *109*, 1–9. [CrossRef]
93. Guo, X.M.; Zhang, Z.Y.; Kang, J.J. Research on the factors influencing energy efficiency in the process of Chinese agricultural mechanization. *Soft Sci.* **2012**, *26*, 51–56. (In Chinese)
94. Zhou, H.; Ran, Q.Y.; Wang, H.S. Analysis on agriculture total factor energy efficiency and its influencing factors in China. *Ecol. Econ.* **2016**, *32*, 133–138. (In Chinese)
95. Ran, Q.Y.; Zhou, H. Research on agricultural total factor energy efficiency under environmental constraints: Based on SBM-TOBIT model. *Econ. Probl.* **2017**, *1*, 103–109. (In Chinese)
96. Yu, H. The influential factors of China's regional energy intensity and its spatial linkages: 1988–2007. *Energy Policy* **2012**, *45*, 583–593. [CrossRef]
97. Hsiao, C. *Analysis of Panel Data*; Cambridge University Press: Cambridge, UK, 2003; ISBN 0-5218-1855-9.
98. NPC. Report on the Seventh Five-Year Plan. Available online: http://www.npc.gov.cn/wxzl/wxzl/2000-12/06/content_1763.htm (accessed on 9 November 2018). (In Chinese)
99. NDRC; MOA. National Vegetable Industry Development Plan (2011–2020). 2012. Available online: http://jiuban.moa.gov.cn/zwillm/ghjh/201202/t20120222_2487077.htm (accessed on 1 November 2018). (In Chinese)
100. Han, H.Y.; Wu, S.; Zhang, Z.J. Factors underlying rural household energy transition: A case study of China. *Energy Policy* **2018**, *114*, 234–244. [CrossRef]
101. Han, H.Y.; Wu, S. Rural residential energy transition and energy consumption intensity in China. *Energy Econ.* **2018**, *74*, 523–534. [CrossRef]
102. Ju, K.; Su, B.; Zhou, D.; Wu, J. Does energy-price regulation benefit China's economy and environment? Evidence from energy-price distortions. *Energy Policy* **2017**, *105*, 108–119. [CrossRef]
103. Zou, B.L.; Mishra, A.K.; Luo, B.L. Aging population, farm succession, and farmland usage: Evidence from rural China. *Land Use Policy* **2018**, *77*, 437–445. [CrossRef]

104. Zhang, Y.Z. Research on the effects of changes in the age structure of China's population to energy consumption: Based on the provincial dynamic panel data by GMM. *China Popul. Resour. Environ.* **2015**, *25*, 69–74. (In Chinese)
105. NBSC. *China Agricultural Machinery Industry Yearbook*; China Machine Press: Beijing, China, 2015; ISBN 977-1-6774-9215-7. (In Chinese)
106. Ram, R. Government size and economic growth: A new framework and some evidence from cross-section and time-series data. *Am. Econ. Rev.* **1986**, *76*, 191–203.
107. Diakosavvas, D. Government expenditure on agriculture and agricultural performance in developing countries: An empirical evaluation. *J. Agric. Econ.* **2010**, *41*, 381–389. [[CrossRef](#)]
108. Greene, W.H. *Econometric Analysis*; Prentice Hall: Upper Saddle River, NJ, USA, 2011; ISBN 978-0-13-513245-6.
109. MOA. *National Agricultural Products Cost-Benefit Data Compilation*; China Agriculture Press: Beijing, China, 1995–2017; ISBN 978-7-5037-8233-6. (In Chinese)
110. Jin, N.; Bao, C.W.; Li, X. Research on the imbalance of the development of agricultural mechanization in China. *China South. Agric. Mach.* **2018**, *4*, 65. (In Chinese)
111. Chen, Y.S.; Hu, H.; Xiao, T.Q.; Cui, S.Y.; Yang, Y.T.; Guan, C.S. Current situation and development countermeasures of mechanization of vegetable production in China. *China Veg.* **2014**, *10*, 1–5. (In Chinese)
112. Yang, M.L.; Bai, R.P. Study on regional unbalance of agricultural mechanization development in China. *Trans. Chin. Soc. Agric. Mach.* **2005**, *36*, 60–63. (In Chinese)
113. Kang, G.G.; Cai, F.; Gao, Q. Development status and countermeasures on mechanized production of vegetables. *J. Chang. Veg.* **2013**, *14*, 69–72. (In Chinese)
114. Tan, C.J.; Yang, S. Problems and countermeasures of agricultural mechanization operation service in Chongqing area. *Res. Agric. Mod.* **2012**, *1*, 78–81. (In Chinese)
115. Cui, S.Y.; Xiao, T.L.; Chen, Y.S.; Cao, G.Q. Analysis of present situation and constraint on mechanized vegetable production in China. *J. Agric. Mech. Res.* **2014**, *10*, 249–251, 256. (In Chinese)
116. Zhang, H.Y.; Hu, K.L.; Zhang, L.J.; Qin, W. Exploring optimal catch crops for reducing nitrate leaching in vegetable greenhouse in North China. *Agric. Water Manag.* **2019**, *212*, 273–282. [[CrossRef](#)]
117. Zhang, D.B. Study on vegetable production efficiency by scale: Evidence from 2009–2016 surveys in main vegetable production areas. *J. Agrotech. Econ.* **2018**, *7*, 41–50. (In Chinese)
118. Taki, M.; Ajabshirchi, Y.; Mahmoudi, A. Application of parametric and nonparametric method to analyzing of energy consumption for cucumber production in Iran. *Mod. Appl. Sci.* **2012**, *6*, 75–87.
119. Chang, J.; Wu, X.; Liu, A.; Wang, Y.; Xu, B.; Yang, W.; Meyerson, L.A.; Gu, B.; Peng, C.; Ge, Y. Assessment of net ecosystem services of plastic greenhouse vegetable cultivation in China. *Ecol. Econ.* **2011**, *70*, 740–748. [[CrossRef](#)]
120. Xiao, T.Q.; He, C.X.; Chen, Q.M.; Chen, Y.S.; Cao, G.Q.; Cui, S.Y. Cost-benefit analysis of vegetable production based on agricultural mechanized production. *Trans. Chin. Soc. Agric. Mach.* **2015**, *46*, 75–82. (In Chinese)
121. Hang, L.M.; Tu, M.Z. The impacts of energy prices on energy intensity: Evidence from China. *Energy Policy* **2007**, *35*, 2978–2988. [[CrossRef](#)]
122. Ma, H.Y.; Oxley, L.; Gibson, J. Substitution possibilities and determinants of energy intensity for China. *Energy Policy* **2009**, *37*, 1793–1804. [[CrossRef](#)]
123. Lu, X.; White, H. Robustness checks and robustness tests in applied economics. *J. Econom.* **2014**, *178*, 194–206. [[CrossRef](#)]
124. Adams, W.; Einav, L.; Levin, J. Liquidity constraints and imperfect information in subprime lending. *Am. Econ. Rev.* **2009**, *1*, 49–84. [[CrossRef](#)]
125. Liu, M.H.; Margaritis, D.; Zhang, Y. Market-driven coal prices and state-administered electricity prices in China. *Energy Econ.* **2013**, *40*, 167–175. [[CrossRef](#)]
126. Luo, X.Y.; Luo, B. Analysis of stakeholders and win-win problem of agricultural electricity price policy. *Issues Agric. Econ.* **2012**, *5*, 59–65. (In Chinese)

